Participation, Representation, and Future Engineers: An engineering-specific examination of capital and inequity in the United Kingdom

by

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A thesis submitted in partial fulfilment for the requirements for the degree of
Doctor of Philosophy
at the University of Central Lancashire

February 2023

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School	**School of Humanities, Languages and Global Studies**

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THESIS ABSTRACT

The United Kingdom faces longstanding challenges within its engineering domain with poor and homogenous participation with educational and career pathways contributing to skills shortages and a lack of diversity amongst UK engineers. These economic and social justice challenges are fundamentally concerned with the same root issue of how individuals can be supported to enter and traverse trajectories to become engineers. Despite significant attention and investment engineering inequities in access, participation, success and representation endure. This thesis therefore identifies a need to develop a more sophisticated and solution-orientated understanding of engineering inequities that can inform impactful interventions to address engineering inequities within the UK.

To develop this understanding the thesis adopts the Bourdieuian capital framework to consider the influential resources that support some individuals to engage with the engineering domain. The experiences of secondary school-aged learners, as the potential next generation of engineers, are examined to develop understanding of engineering inequities within the UK. Data is collected from 921 secondary school-aged learners from England and Scotland through a questionnaire methodology to investigate the forms of supportive resource that align to engineering inequities. The science capital model developed by Archer and colleagues is identified as an influential capital-based perspective on inequity in the science domain. This model is critically investigated and found to lack a practical relevance to engineering but is adopted as an influential template through which to develop a richer, engineering-specific understanding of inequity.

A four-stage model and instrument development process is then undertaken to create the engineering capital model and instrument: a tool capable of examining the engineering resources that underpin engineering inequities between groups. A theoretical model of engineering capital is first created through a critical synthesis of existing literature. This model includes forms of cultural capital, social capital and behaviours and practices that can support engineering educational or career aspirations. A quantitative instrument of engineering capital is then created through data reduction and regression analyses. The instrument is found to be a valid perspective on engineering inequity that aligns to current understanding, offers new insights and can reasonably predict the engineering aspirations of learners. This thesis offers a number of valuable contributions to support greater understanding and intervention with the engineering inequities underpinning skill shortages and diversity challenges in the UK. The theoretical model of engineering capital unifies distinct strands of previous study under a common, unifying framework and so offers a rich conceptualisation of how individuals are supported to become engineers. The empirical instrument is capable of measuring the engineering capital of young learners to identify the degree to which individuals are supported with resources that facilitate future engineering trajectories. This operationalisation facilitates a more nuanced understanding of engineering inequity beyond simplistic descriptions that rely on gender, ethnic, or social class groupings. The forms of capital identified as significant within this model and instrument may be drawn on to inform interventions to address inequity and support a larger and more diverse population of future engineers.

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ACKNOWLEDGMENTS

I would not have been capable of completing this thesis if not for the kindness, wisdom and support of a great many people.

Firstly, I would like to sincerely thank my supervisors Dr Richard Davies, Dr Liz Granger and Dr Jo Trowsdale who have offered both academic and personal guidance throughout this journey; your mentorship has challenged and nurtured my skills as a researcher and I am endlessly grateful for your kind support.

I wish to thank the University of Central Lancashire for funding this PhD project and the many colleagues who have enabled the completion of my studies. In particular, I must thank Maggie Maclean, Nicky Danino and Dr Cherry Canovan for their encouragement.

I would like to thank the team at Primary Engineer for their aid in establishing this project and promoting participation within their network. Particular gratitude is due to Susan Scurlock who has both assisted and championed this body of work with an infectious motivation to support future engineers.

A great many thanks are owed to the schools, teachers and young learners who have participated with this research project despite the enduring impact of the Covid-19 pandemic – thank you for your time and efforts.

And finally, I owe more thanks than I am capable of expressing to my friends and family. Thank you to my mother, Karen, for decades of ceaseless encouragement – I doubt very much I would have undertaken this challenge without your belief in me. And thank you to my partner, Alex, for your unwavering patience, confidence and care – your support has truly kept me going and I am lucky to have you.

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INTRODUCTION

This thesis explores the topic of engineering inequity – patterns of access, participation, representation and success – within the UK engineering domain to better understand how young learners are supported to become future engineers. The thesis aims to advance current understanding of how young learners are supported to become engineers in a manner which may inform interventions and support greater equity amongst future engineering cohorts. This is addressed through two research questions:

1. Does the science capital model, as a widely acknowledged model of science inequity, also apply to the engineering domain?

2. Is it possible to draw on a domain-specific application of Bourdieuian capital to develop an engineering-specific model of capital that will fulfil the aim of this project and increase understanding and intervention of engineering inequities in the United Kingdom?

The United Kingdom faces longstanding challenges within its engineering domain with poor participation with educational and career pathways contributing to skills shortages and, with the homogenous nature of those engaging, a lack of diverse representation amongst UK engineers. Over 200,000 more engineering-skilled individuals are required each year to meet demand projections, whilst the profile of those who do enter engineering roles is highly restricted: only 16.5% of those in engineering roles are women and only 11.4% belong to non-white ethnic groups (EngineeringUK, 2018; EngineeringUK, 2022). This pattern of limited and uneven participation and representation is present throughout educational and career pathways for engineering highlighting a systematic problem of engineering inequity within UK society.

Such inequities are understood as entrenched patterns of access, participation, success and representation that see some groups favoured over others, leading to varied relationships with the engineering domain. This can take many problematic forms such as unequal representation within engineering workforces or unequal levels of access to, or success in, engineering education. Gender, ethnic and social class inequities are well-established within the engineering domain, skewing to a dominant engineering profile of white males from more privileged socio-economic backgrounds (EngineeringUK, 2018; 2018a; 2018b). The intersectional inequities of engineering are less well established within the current literature but are recognised in this thesis as an important nuance underlying support for future engineers.

Engineering inequities pose a complex and significant threat to economic wellbeing and social justice within the UK. In 2015 engineering industries contributed over £420 billion to the UK economy, highlighting both the national importance of this domain and the potential economic threat caused by an insufficient supply of future engineers (EngineeringUK, 2018). The lack of diversity within the engineering domain also contributes to social injustice with many groups experiencing inequitable access to a respected, secure and well-paying employment domain challenging the fairness within UK society. Engineering inequities are therefore not only an issue within the engineering domain but represent a fundamental threat to the economic and social wellbeing of the nation. Given the key role of engineering within efforts to address climate change, global health and standards of living, the impact of engineering inequities may even be considered an existential threat to global resilience.

Within the UK, challenges of engineering inequity in educational and career contexts continue despite significant attention and investment. These inequities are long-recognised with government reports examining this topic over several decades (Department for Business Innovation and Skills, 2013; House of Commons Committee of Public Accounts, 2018; UK Government, 1993). Successive governments have invested to address this problem with almost one billion pounds spent between 2007 and 2017 to support STEM skills and new pathways to engineering skill development introduced for school and working-age people (Department for Education, 2021; National Audit Office, 2018). The continuing need for greater participation and wider representation amongst UK engineers, despite this attention and investment, highlights the need for more focused contemporary study to better understand and overcome these longstanding challenges. In particular, there is a need to better understand how younger generations are supported to become the next cohort of UK engineers given the early indications of engineering inequity amongst young learners (Education Datalab, 2022; Hutchinson & Bentley, 2011; Institution of Mechanical Engineers, 2017).

A problematic lack of understanding and effective interventions to develop greater engineering equity is therefore identified. This thesis addresses this challenge through a rigorous exploration of engineering inequity amongst secondary school-aged learners to develop a richer understanding of how these learners are supported to become engineers.

To accomplish this, the capital framework of Pierre Bourdieu is adopted as a lens on the distinctions that underpin engineering inequities. The concept of ‘capital’ considers the possession of particular resources which provide advantages to the possessor and denote the distinction between social groups. An individual in possession of appropriate capital can reproduce their social position with Bourdieu originally applying this concept to examine the cultural and social resources that perpetuate the intergenerational reproduction of social class. The concept of capital can thereby provide a theoretical and empirical structure to examine group inequities by critically considering the underlying distribution of resources. Within this thesis, Bourdieuian capital is adopted as an interpretative tool to investigate and develop understanding of the resources that underpin current engineering inequities. This adoption is practically-orientated with the capital concept adopted as a research tool to develop greater understanding. Whilst Bourdieu's framework is nuanced and sophisticated, this thesis will focus on the issue of engineering inequity as opposed to the deeper theoretical or philosophical nuances of the Bourdieuian perspective.

To accomplish this the thesis is structured around two main lines of enquiry. The first explores whether the science capital model, as a widely acknowledged model of science inequity, also applies to the engineering domain. This is examined theoretically and empirically in Chapters Two and Four. The second line of enquiry considers whether it is possible to draw on a domain-specific application of Bourdieuian capital to develop an engineering-specific model of capital that will fulfil the aim of this project and increase understanding and intervention of engineering inequities in the United Kingdom. This is examined in Chapters Five to Eight. The following summaries outline the narrative of this thesis and its development of greater understanding of engineering inequities in the UK.

In *Chapter One: Defining an Inequitable Domain,* the engineering domain of the United Kingdom is explored to frame current understanding of engineering inequities and the context in which they occur. First, a definition of engineering is formed through a synthesis of varied perspectives recognising that 'engineering' is conceptualised differently by different groups. This definition frames engineering as a practice of creative problem solving, commonly understood as 'making and fixing' but that can be more deeply understood as activities involving established design processes with the objective of creating effective and efficient solutions to identified problems. Engineering is recognised as somewhat related to – but not the same as – other domains such as science, technology or mathematics. Next, the historic and contemporary role of engineering in the UK is explored to contextualise the engineering domain and its significant influence on UK society and culture. Engineering is positioned as culturally entrenched, historically and contemporarily, within UK society but undergoing a period of transition which challenges the cultural and social understanding of this domain. The need for a culturally sensitive perspective is therefore identified to better understand engineering inequities. Finally, systemic patterns of poor and inequitable participation and representation within engineering educational and career contexts are explored highlighting significant challenges to the functioning and fairness of the UK engineering domain.

This analysis identifies a need to better understand how individuals are supported to become engineers to proactively address both an insufficient number of UK engineers and the limited diversity within this group which skews to a white, male dominance. The need to better understand the engineering development of young people, as future engineers, is highlighted as particularly important given the early indications of engineering inequity noted in past research. The objective of this thesis is thereby identified: to build on limited understandings of engineering inequity to better understand how individuals can be supported to access and participate with engineering educational and career pathways.

In *Chapter Two: Finding Engineering in Science Capital,* the 'science capital' model of science inequity is critically considered as a potential tool for adoption within this thesis to develop a stronger understanding of engineering inequity. This model offers a contemporary and sophisticated understanding of inequity within the science domain drawing on the concept of 'capital' developed by Pierre Bourdieu as an influential form of resource that delineates advantages to some groups. The definition of engineering developed within Chapter One notes a relationship between engineering and science raising the potential adoption of science-based perspectives to better understand engineering inequities. The capital perspective adopted within science capital is compatible with the need, also identified in Chapter One, to adopt a culturally sensitive perspective to understand engineering inequity. First, the science capital model is introduced highlighting its value as an innovative lens on inequity and its compatibility with the objective of this thesis to develop a more nuanced understanding of inequity in a STEM (Science, Technology, Engineering, Mathematics) domain. Next, the theoretical model of science capital is deconstructed and critically analysed in relation to wider literature to examine its scope in relation to engineering. This analysis explores how seven key elements of science capital may relate to patterns of aspiration for future engineering amongst young learners. Finally, these analyses conclude that whilst the underlying Bourdieuian capital approach to framing inequity may apply to engineering a measurement of capitals for science may lack the specificity to also represent the engineering domain. This analysis therefore questions the degree to which the science capital model can serve as an effective lens on specific patterns of engineering inequity. However, it is noted that this conclusion should be tested empirically to confirm this lack of relevance and explore the potential formation of an engineering-specific capital model of inequity.

In *Chapter Three: Methodology,* the research methodology of this thesis is outlined. A conceptual framework first defines the interpretation of 'engineering', 'inequity' and 'Bourdieuian capital' adopted within this thesis. A pragmatic research methodology is then established to empirically investigate engineering inequity in the UK through a questionnaire-based research design. This methodology involves the empirical investigation of science capital as a lens on engineering inequity and, should that model be found to be inadequate, the development of an engineering-specific model of capital. Due to the impact of the Covid-19 pandemic it was necessary to conduct only a single point of data collection to maintain safety and minimise impact of participation. Secondary school-aged (11-16 year old) participants were sampled due to the engineering inequities present at this age, the previous use of science capital with this group, and potential for early intervention to equitably support the coming generation of UK engineers. Aspirations to future engineering education and careers are adopted as an age-appropriate form of engineering inequity that indicates trajectory towards future engineering involvement. The materials, procedure and methodological limitations of this research methodology are also documented and explored.

In *Chapter Four: Testing Science Capital for Engineering Inequity,* the theoretical conclusions outlined in Chapter Two are empirically tested to determine the relevance of science capital in understanding patterns of engineering aspiration amongst young learners. Science capital is empirically measured amongst the thesis sample utilising an existing instrument; the items of this instrument are also ‘translated’ to focus on the engineering domain to create the ‘Archer-style engineering capital’ instrument as a comparable, engineering-specific measurement tool. Patterns of responses on these instruments are examined in relation to engineering aspirational inequity with analyses supporting the theoretical conclusions of Chapter Two that question the relevance of science capital as a lens on engineering inequity. However, these analyses also reveal that a capital-based domain-specific perspective is valuable, with the simplistic ‘Archer-style engineering capital’ instrument aligned more strongly with patterns of engineering inequity and offering novel insights as to the nature of engineering inequities in the UK. This chapter thereby validates the development and application of a more sophisticated engineering capital model to accomplish the objectives of this thesis in developing a greater understanding of engineering inequities.

In *Chapter Five: Forming a Theoretical Model of Engineering Capital,* a four-stage instrument development process is introduced to create an engineering-specific capital perspective on engineering inequity. The methodological approach used to form the science capital model is critically reviewed in relation to instrument development literature and then adopted. This four-stage process included: the formation of a conceptual framework, the development of a theoretical model, the creation of an empirical measurement instrument and the validation and testing of this tool to confirm the utility of the developed engineering capital model. The first two stages of this process are completed in this chapter. First, a conceptual framework of engineering capital is outlined before a theoretical model is formed drawing on past literature. This model considers how forms of capital such as engineering literacy, engineering attitudes, or knowledge of engineering pathways align with patterns of engineering aspirational inequity amongst young learners. The aggregation of past findings within a capital framework offers a sophisticated theoretical perspective of engineering inequity in line with the objectives of this thesis. This approach also supports the development of measurement tools to assess the engineering capital of young learners in later stages of the adopted development process.

In *Chapter Six: Creating an Engineering Capital Instrument,* the third stage of the adopted instrument development process is undertaken to form an empirical instrument capable of measuring engineering capital drawing on the conceptual framework and theoretical model created in Chapter Five. An empirical instrument capable of measuring engineering capital facilitates both a validation of this novel perspective and the accomplishment of the thesis objective in developing more detailed understandings of engineering inequity in the UK. First, questionnaire items are developed for each form of engineering capital included in the theoretical model, drawing on novel items and existing research tools. Next, data collection is undertaken with this questionnaire to empirically measure the forms of capital included in the engineering capital theoretical model. Finally, statistical analyses are utilised to refine the broad data collection questionnaire to form a concise instrument measuring the most indicative forms of capital to distinguish those with greater or lesser engineering capital. This instrument represents a key output of the thesis and an important tool capable of meeting the thesis objective of developing greater understanding of engineering inequity.

In *Chapter Seven: Validating and Exploring Engineering Capital,* the fourth stage of the instrument development process is undertaken to validate the engineering capital instrument created in Chapter Six. This validation is essential to confirm that the created model and instrument is aligned to engineering inequity and thereby represents a valuable tool. First, engineering capital scores are calculated for the thesis sample using the engineering capital instrument. Next, statistical tests confirm that engineering capital is positively associated with greater educational and career aspirations for engineering, as well as aligned with past understandings of engineering inequity, and can be used to significantly predict whether young learners wish to study or work in engineering roles in the future. These findings validate that engineering capital is a useful lens on engineering inequity that aligns with past understanding and can be used to develop greater understanding and intervention with the longstanding inequities within the UK engineering domain. Finally, the characteristics and responses of those with high and low levels of engineering capital are reflected on to highlight the fundamental importance and wide influence of engineering capital as an indicator of how individuals relate to the engineering domain.

In *Chapter Eight: Further Dimensions of Engineering Capital,* further forms of engineering capital are theoretically and empirically considered in relation to engineering inequity recognising that the model and instrument of engineering capital developed within this thesis is only one possible structure of engineering capital. Five further dimensions of engineering capital are explored including forms of capital not included in the initial model and learner engagement with the engineering domain. The four further forms of capital included in this examination are found to positively align with the developed engineering capital model supporting its rigour and representativeness as a capital lens on engineering inequity. The fifth dimension, engineering learner engagement, is also found to positively align with the model supporting that engineering capital can also be used to understand inequities within learning contexts and experiences.

Finally, a *Conclusion* chapter draws together the key findings of this thesis. The objective of the thesis is reflected on and judged to have been met through the development of the engineering capital lens which offers a theoretical and empirical perspective through which engineering inequities can be better understood. The limitations of this thesis are explored alongside future avenues of research and intervention to overcome engineering inequities entrenched within the United Kingdom.

CHAPTER ONE: DEFINING AN INEQUITABLE DOMAIN

Introduction

In Chapter One the UK engineering domain will be explored to establish a foundation of knowledge and frame the objective of this thesis: to develop greater understanding of engineering inequities to support wider participation and diversity amongst future engineers. First, a definition of engineering will be critically synthesised recognising that varied conceptualisations of engineering are present amongst the population. Next, the historic and contemporary context of engineering will be examined to situate this body of research and recognise the complex cultural and social characteristics aligned to the engineering domain. Finally, this definition and contextualisation will support an exploration of the inequities that challenge the engineering domain, particularly highlighting the threat these pose to coming generations of engineers. The critical consideration of these three topics will situate the objective of this thesis by identifying a need for more sophisticated understanding of entrenched and complex engineering inequities.

Defining Engineering

Establishing a definition of engineering is not a simple task: no universal definition of 'engineering' is agreed upon in either popular usage or academic literature despite the wide-spread practice and impact of this domain in contemporary societies. The practices and cultural concepts of engineering may differ too greatly between local, national and international contexts for a singular global definition of engineering to exist. However, for this thesis to effectively examine engineering and its issues in the United Kingdom a working definition is required. To form this working definition a critical synthesis of literature was conducted unifying four distinct approaches to defining engineering.

The 'Common' Understanding of Engineering in the UK Context

First, the common conceptualisation of engineering amongst the UK population can be considered as a de facto, socially constructed definition of engineering. Although little literature monitors the conceptualisation of engineering amongst this population, a definition of 'making and fixing things' is acknowledged as particularly common (Institution of Mechanical Engineers, 2016; Institution of Mechanical Engineers, 2017; Lucas et al., 2014; Marshall et al., 2007). The dominance of this simplistic view of engineering is supported by wider explorations of the perceptions of engineers and engineering in the UK and overseas (Fralick et al., 2009; Hammack et al., 2015; Silver & Rushton, 2008). 'Making and fixing' is so prevalent within public definitions of engineering that even those who report possessing a high level of engineering understanding will misidentify a definition of engineering that lacks these descriptors as instead defining 'science' (Marshall et al., 2007). The confusion between science and engineering amongst the general public is noted elsewhere with only half of UK adults in one sample viewing the two domains as different (Castell et al., 2014). The simplicity of the dominant, socially constructed definition of engineering as 'making and fixing' should not be surprising given the notedly poor public literacy for engineering expressed within the UK (Institution of Mechanical Engineers, 2016; Institution of Mechanical Engineers, 2017; Marshall et al., 2007). A public-led approach to defining a domain is inherently impacted by the scope of understanding present amongst the population. In the case of engineering in the United Kingdom evidence suggests that a social constructionist approach risks collating misunderstanding or ignorance due to poor levels of engineering literacy. This challenge fundamentally questions the notion that 'making and fixing' is an adequately rich definition for adoption within this thesis. The validity of this criticism is clear when examining what other practices also fit under the definition of 'making and fixing': painting, baking, or tidying a room could fit beneath this framing depending on how strictly it is interpreted. The socially constructed definition of engineering as 'making and fixing', whilst beneficial as common and accessible, lacks the granular scope to isolate practices that would be institutionally considered as engineering such as construction, manufacturing or telecommunications. This would suggest the need to adopt alternative strategies to supplement this approach and define engineering in sufficient detail.

An Expert-Led Perspective on Defining Engineering

In response to the limited understanding of the general public, a second approach to defining engineering might consider the insight of experts such as engineers or academics who are more intimately involved in the engineering domain. Though not rooted in 'common' understanding the perspective of these minority groups may supplement the 'making and fixing' definition with further distinguishing characteristics of engineering. A synthesis of sources supports the value of an expert-led strategy to defining the characteristics of engineering. One such identified characteristic is the relationship between technology and engineering practices. The use of technology as a defining characteristic of engineering is acknowledged by academics, engineers and some of the general public (Crawley et al., 2007; Davis, 1996; International Engineering Alliance, 2013; Marshall et al., 2007). The important presence of technology and its use in practices of engineering can clarify the scope of the less sophisticated 'making and fixing' definition by rejecting forms of 'making and fixing' that lack this technological aspect such as 'painting, baking or tidying a room'. As a result, 'use of technology' can assist in defining the engineering domain.

This relationship with technology is built upon by Pleasants and Olson (2018) who frame engineers as not only the users, builders, or fixers of technology but as the designers of technology. This acknowledges making/'building' and fixing but also introduces the vital addition of 'design' that is not explicitly relayed within the 'making and fixing' definition. Design within an engineering context is presented as a process of creation that results in successful objectives and value (Chou & Chen, 2017; Dorst & van Overveld, 2009). Engineering design is introduced as a distinct practice of design that can further distance the conceptualisation of engineering from more general 'making and fixing' (Pleasants & Olson, 2018). Whilst an artist may also be a 'designer' the required skills, knowledge and embodied traits specific to artistic or engineering design distance these practices in such a way that an artist is likely unable to effortlessly transfer to an engineering design setting (Eder, 2012). 'Design' is thereby not a singular process but one dependent on context. Within the engineering domain design is specifically motivated: engineers possess utilitarian values and objectives of effectiveness and efficiency in problem solving that steer the process of design, making and fixing (Mitcham, 2006) whilst artists are instead motivated by artistic expression and conveying meaning (Carroll, 2012). The importance of design within a working definition of engineering is further supported by the recognition of the Engineering Design Process as a fundamental and prescribed practice of engineering involving creative problem solving through a formal engineering procedure. In this key guiding process for engineering a problem is first identified, key design principles to propose effective and efficient solutions are devised, prototypes and ideas explored to identify the strongest approach, which is then realised, tested, and iterated to from an effective actioned solution (Dym et al., 2005; Haik, 2015; Winarno et al., 2020). The principles and structured practice of the Engineering Design Process is a norm within engineering that establishes methods and expectations for engineering behaviour and so can be used to characterise the domain (Daly et al., 2018). The recognition of these characteristics by experts assists in the framing of engineering beyond the simplistic 'making and fixing' definition.

The traits of engineers can also be considered to form a richer conceptualisation of 'engineering' than the simplistic 'making and fixing'. Engineers may be understood as products of experience and institutional processes to select and perpetuate successful engineering practice. As a result, the qualities of engineers such as their knowledge, skills, values, competencies and other personal characteristics may be considered as embodied qualities of engineering that supplement its definition. Wider literature identifies engineering characteristics such as a systematic thinking (the ability to recognise interconnectedness of the world and elements of larger structures) or collaborative social strategies (a capacity for team working central to engineering processes and success) as key within engineering practices (National Academy of Engineering and National Research Council, 2009). Further characteristics are also acknowledged such as creativity (which is inherent to the creation of engineering products or proposed solutions to engineering problems) or innovative thinking (as a form of effective and valuable novelty) (Daly et al., 2018; Institution of Mechanical Engineers, 2016). This link to creativity is particularly acknowledged within the engineering domain, despite a preconceived notion of its ‘logical’, ‘scientific’ or ‘mathematical’ nature (Cropley, 2016; Thompson & Lordan, 1999). Other researchers have explored proficiencies as engineering ‘ways of thinking’ which may support an understanding of engineering as defined through its embodiment; visualising, improving, problem finding or resilient adaptability are identified as embodied within those who successfully complete engineering practice (Grubbs et al., 2018; Lucas et al., 2014). These embodied definitions of engineering can provide a rich and human-focused definition that is deeply compatible with the scope of this thesis and its understanding of how future engineers are supported to develop.

The expert-informed approach to defining engineering through its practices and embodied characteristics can clearly provide greater nuance beyond the simplistic framing of ‘making and fixing’. As those most acquainted with the engineering domain the perspective of engineers and academics can be understood as more valid than those of the poorly informed public supporting the adoption of these characteristics within a working definition of engineering. However, the approach used to form these perspectives on engineering must be critically considered. First, the objectivity of these perspectives must be questioned: drawing on the views of current engineers is an exclusionary approach taking on a limited range of experiences. Only those who have successfully navigated the journey into engineering study or practice offer their insight in these perspectives thereby excluding alternative views of engineering. An expert-informed approach can thereby be understood as lacking in dissenting views and suggests that the resulting perspective on engineering characteristics is a dominant definition of engineering rather than a broad or divergent perspective. Whilst this does not discount the use of these characteristics when defining engineering the homogeneity of these sources and the resulting definition must be considered as self-fulfilling and a perpetuation of the status quo framing of engineering. A definition drawn from such a small subset of individuals may also be at odds with the notably poor understanding of the wider public and therefore incompatible with efforts to change public literacy for this domain.

It must also be considered that expert-informed approaches to defining engineering are not universal – cultural differences in the practice and profession of engineering can vary the characteristics identified. Previously published comparisons of national engineering employability standards highlight both commonality and dissent in how engineers are benchmarked (and so how engineering is embodied in practice) between national contexts. Characteristics such as creativity and design-led processes are commonly identified across national contexts, supporting some of the characteristics identified in the expert-led approach outlined above. However, distinctions in the framing of engineering standards are also present such as a need for a 'balanced personality' and 'entrepreneurial mind' within Japan or a 'willingness to take risks' and 'service to others' in the European Union context (Zarharim et al., 2010). This international variety in how engineering practices are institutionally recognised supports the social constructionist position that no singular definition of engineering exists for all contexts. As a result, the defining characteristics of engineering offered by experts must be understood as situational and so mindfully adopted. This inherent subjectivity is also demonstrated in the universally positive nature of engineering characteristics identified by experts: none of the characteristics outlined from literature above include negative traits of engineers. As human actors it is unreasonable to expect engineers (and their embodiment of engineering) to be wholly positive, suggesting that the positive characteristics of engineering offered by experts are an incomplete (and thereby potentially skewed) representation of the domain. It is possible that former engineers, as an alternative body of experienced individuals within the engineering domain, may characterise engineering differently. The valuable perspective of former engineers is previously established in past literature but not used in defining the domain (Fouad et al., 2011). The lack of insight from these groups in such definitions further highlights the bias within expert-framed definitions of engineering. These critiques demonstrate the need for wariness in adopting expert-led definitions of engineering. However, given the proximity of these individuals to the engineering domain and the limited understanding amongst other groups these perspectives may still offer cautious value in framing a working definition of engineering.

The Linguistic Perspective on Framing Engineering

An alternative approach to defining engineering that limits this potential bias of selective sampling is the adoption of linguistic analysis in framing the engineering domain. Rather than forming a definition of engineering based on its practices (such as with the common 'making and fixing' definition, or in terms of expert framed understandings of engineering design processes) this linguistic approach instead forms a definition of engineering based on its use in language. A linguistic analysis may consider the content of speech or written communication to understand what is meant and how this meaning is conveyed in linguistic expressions (Gee, 2004). For example, the root of the word ‘engineering’ can be examined to understand its cultural and historical context. The Latin roots of the word ‘engineering’ are ‘ingenium’ meaning ‘cleverness’ and ‘ingeniare’ meaning ‘to contrive or devise’ highlighting links between engineering and concepts of sophisticated design. Later origins in Middle English connotate ‘enginour’ with activities of designing and operating military equipment and practices of crafting and mechanisation reflecting both the common practices of engineering at the time and the cultural foundations of modern engineering (Lew & Kingery, 1918; Oxford Dictionaries, 2022). This linguistic approach has been applied to consider the contemporary synonyms and cognates of ‘engineering’: Mitcham and Mackey (2009) offer that associated terms such as “investigation, innovation, design, technology or science” (p55) can be used to understand the interconnectedness and conceptual context of engineering. Notably, several of these examples (innovation, design, technology, science) have been highlighted in the earlier public and expert-led approaches to defining engineering supporting the credibility of this linguistic approach. Such a linguistic perspective can be understood as, like language, socially constructed and sensitive to contextual use so must be critically considered with questions as to the validity of this approach beyond English language contexts. Different languages may conceive of engineering differently in response to the cultural contexts of these languages, questioning how universal a definition of engineering might be if formed through this linguistic approach. This criticism of context dependency may also apply within English language settings with little consideration of regional dialects and linguistic characterisations that may delineate distinctions in how engineering is conceived of. This is a particular issue in the United Kingdom due to both its recognised regional linguistic character and its regional engineering history (Hudson & Hudson, 1989; Hughes et al., 2013). As a result, the linguistic definition of engineering may be criticised as yet another status quo or dominant cultural framing of engineering. Despite these criticisms the linguistic approach to defining engineering can be useful and offers further elements and nuance for cautious consideration beyond the simplistic ‘making and fixing’ definition. The consistency of the linguistic approach to the positioning of the socially constructed and expert-led framings supports the validity of a definition formed through this analysis.

Finding a Further ‘Relational’ Perspective on Defining Engineering

The synthesis of common, expert and linguistic perspectives on the definition of engineering offers a richer conceptualisation than any one approach might provide alone. The dominant public view of engineering as ‘making and fixing’ is accessible but notably lacks detail which challenges its operational value for adoption in this thesis. Expert-led insights can offer greater nuance such as the importance of technology, specialised design processes and embodied characteristics of creativity or systems thinking in practices of effective and efficient problem solving. The linguistic approach aligns with these previous findings identifying a link between engineering and design, innovation, science, technology and ‘cleverness’ of creation. The synthesis of common, expert and linguistic definitions provides a framing of engineering that bridges both the dominant socially constructed understanding of engineering with expert insight and historical and contemporary cultural representation of engineering. The consistency established between these framings of engineering supports the value of this synthesised understanding of engineering and its adoption within this thesis.

This synthesis of approaches also repeatedly raises the importance of framing engineering in connection to other domains – particularly those of the STEM (Science, Technology, Engineering, Mathematics) grouping. Expert-led framings of engineering identify a nuanced connection to technology where engineers both design and apply technology within engineering activities (Pleasants & Olson, 2018). A relationship between engineering and science is identified both in the conceptualisations of the general public and in the linguistic approach to defining engineering (Castell et al., 2014; Mitcham & Mackey, 2009). The insight of experts also identified a relationship between engineering and creative domains (Cropley, 2016; Institution of Mechanical Engineers, 2016; Thompson & Lordan, 1999). This synthesis thereby introduces a fourth ‘relational’ approach to defining engineering in relation to other domains.

A critical examination of STEM domains highlights the interconnectedness of engineering to science, technology and mathematics. The STEM acronym can be understood as a deeply prominent linguistic expression which perpetuates a sense that the four domains are interconnected (Akerson et al., 2018). Collectively these subjects are considered to be rational and logical (Quinn et al., 2020) and at odds with more artistic and subjective domains such as art or the humanities (representing yet another ‘relational’ approach to forming a definition). The connection between engineering and STEM is not only linguistic but also institutionally enforced in the UK context: the study of engineering in higher education will frequently require qualifications in science or mathematics. This demonstrates not only a *likening* of engineering and STEM domains but an enforced *dependency* on this interconnectivity. This culturally and institutionally enforced relationship between engineering and STEM contributes to a blurring of distinction between these domains and supports an interconnectedness within society (Janich, 1978). The association between engineering and science is further supported by alignments in the embodiment and practices of these domains. Characteristics such as rationality, logic and sceptical questioning are applied both in practices of hypothesis formation in science and ‘problem finding’ in engineering (Çalik & Coll, 2012; Duschl & Bismack, 2016; Lucas et al., 2014). The nature of engineering and science thereby share commonalities that relate (and confuse the distinctiveness of) the two domains (Antink-Meyer & Brown, 2019). This interconnectedness is arguably more obvious within the professional domain which, unlike the educational context, does not operate in subject area silos. Scientists and engineers may occupy the same contexts or cooperate in a collaborative fashion. Practices of ‘applied’ or ‘practical’ science, defined by Nils Roll-Hansen (2009) as “dedicated to the solution of practical economic, social and political problems rather than the further development of such knowledge and methods” (p3), are starkly similar to the objectives of engineering (creative problem solving) though it must be noted that further defining characteristics of engineering such as the Engineering Design Process or engineering traits are not essential within applied science limiting the overlap between domains. Applied science is also recognised as distinctly different from the more traditional ‘theoretical’ science of knowledge development highlighting the place of ‘applied science’ as a bridging construct between science and engineering domains (Roll-Hansen, 2017). These interdependences of science and engineering in real world practices further draws together the interconnectedness of these domains supporting a rationale of conceptualising engineering in terms of relational links to science, technology and mathematics.

The interconnectedness of engineering and other STEM domains is also validated in educational contexts. Though present in only a limited fashion in UK classrooms, international educational literature acknowledges the validity and impact of removing subject area siloes in ‘STEM integrative’ pedagogies (English, 2016). These approaches to STEM learning draw on commonalities between STEM subjects to develop richer learning experiences through co-subject learning. Engineering is particularly important in these pedagogical approaches with the Engineering Design Process adopted as the pedagogical structure to integrate subject knowledge and practices of science, technology and mathematics (English, 2020; English, 2021). As a result, engineering is frequently present in STEM integrative pedagogies (Li et al., 2019). The perspective of this literature offers two valid insights: that engineering shares similarities with STEM domains to a degree that allows effective integration in multidisciplinary learning and that engineering is particularly more open to integration with other domains (Quinn et al., 2020). This quality of ‘openness to integration’ offers a further characteristic of engineering that supports its connectedness to other STEM domains – but also, paradoxically, highlights a distinction in its character in comparison with other STEM subjects that are less commonly used as vehicles of integration.

This paradoxical similarity and difference demonstrates the complexity within the relational links between engineering and STEM. Despite the identification of many commonalities, it is also possible to distinguish engineering from other STEM domains. For example, the goals and motivations of engineering and science are clearly distinct: where engineering practice is orientated to real-world problem-solving, science instead focuses on robust and rigorous advancement of knowledge (Poser, 1998). The two domains can also be seen to differ epistemologically with science orientated to the pursuit of truth whilst engineering is instead focused on utility and usefulness of knowledge (Grimson & Murphy, 2015; Kant & Kerr, 2019). The priorities of engineering thereby focus on effectiveness and efficiency in a manner that does not apply to science. This is articulated by Skolimowski (1966) who argues that despite similarities engineering and science operate to accomplish fundamentally different effects. Although the co-occurrence of engineering and science was offered earlier as support for the similarities between science and engineering an examination of the formal processes involved in each context can also distance these domains. For engineering this is the Engineering Design Process, the cyclic process of identifying a problem and working to a solution through iterative design (Dym et al., 2005; Haik, 2015; Winarno et al., 2020). For science this is the Scientific Method, the process of determining a hypothesis and testing this to establish understanding (Carey, 2011). These processes are superficially similar in that they are structured, linear and organised however otherwise they are very different in the objectives they work towards, principles that they observe, contexts in which they occur, actors who participate, and motivations for accomplishment (Cross et al., 1981). This deeper lens on practices demonstrates that superficial similarities may betray deeper distinctions highlighting the importance of critical examination in understanding the definition of engineering. In real world application science and engineering are thereby tremendously different practices for scientists and engineers.

The distinctiveness of engineering is also clear in explorations of how the UK population view and interact with STEM domains. Knowledge and interest in science is much greater than that reported for engineering demonstrating that these individuals do not view science and engineering as the same (Castell et al., 2014; EngineeringUK, 2018; Institution of Mechanical Engineers, 2016; Institution of Mechanical Engineers, 2017; Marshall et al., 2007). These distinctions are also noted amongst younger generations with lower interest, value and career aspiration for engineering compared to science, technology and mathematics (Hutchinson & Bentley, 2011). The ability to distinguish these domains in relation to knowledge, attitude, engagement and aspirations demonstrates that these areas are not identical supporting the prepositions that they differ and that culturally the UK population is skewed to favour science. These findings further demonstrate the distinctions within the STEM grouping that isolate engineering from other domains and question the uncritical adoption of the STEM acronym and its presumptions of similarity.

Though at times self-conflicting the similarities and differences of engineering to other domains can aid in scoping a working definition of engineering within this thesis. This fourth approach to defining engineering introduces greater disagreement than previously congruent socially constructed, expert-led and linguistic approaches. However, it is possible to integrate these disparate similarities and differences through the adoption of a ‘positional’ perspective that accounts for the context in which these comparisons are made. The relationship between engineering and other STEM domains could be understood as a ‘family resemblance’ drawing on the work of Wittgenstein (1969) who recognised that commonalities can be multidimensional but not exclusive. For example, poker and football might be considered as within the ‘family’ of ‘games’ and share characteristics (both are games, are competitive, and can provide prestige and profit at expert levels) as well as differences (one is a ball sport whilst the other is a card game, one is played as part of a team whilst the other is played without a team, one depends more on physical attributes whilst the other relies on mental capacities). The concept of family resemblance allows comparisons to recognise shared traits (as between members of a family unit) but does not dictate perfect, exclusive replication of all qualities. With this perspective it is possible to move beyond a binary consideration of engineering and other domains as either ‘the same’ or ‘different’ and recognise that the comparative similarity of two domains will depend on the specific position from which comparisons are made (i.e. a positional relationship). In this way engineering and science may appear similar from a position drawing on traits of rationality or logic but will appear differently from a position of formal practices or core motivations. A positional interpretation also supports the integration of less informed general public and more informed expert definitions of engineering as originating in two distinct contexts with distinct levels of understanding. This perspective allows the synthesis of positions and shifts the burden from judgements of the engineering domain to judgements of the context in which a comparison with this domain is made. In this way it is possible to recognise the valid and opposing positions that both relate and distance engineering from other STEM domains and enforce a need within this thesis to clarify the position from which these subjects are compared within the definition of engineering. This perspective further demonstrates the socially constructed and cultural characteristics of defining the engineering domain.

A Working Definition of Engineering

A critical synthesis of literature has demonstrated that no one singular definition of engineering exists, nor can any one source offer a full accounting of the engineering domain, however through a synthesis of literature it is possible to aggregate perspectives to assemble a working understanding of engineering for use in this thesis. Although not positioned as an exhaustive framing of engineering this definition is suitably nuanced to support the objectives of this research in understanding engineering within the UK context.

This aggregated approach can define engineering as: a practice of creative problem solving, commonly understood as 'making and fixing' but that can be more deeply understood as activities involving established design processes with the objective of creating effective and efficient solutions to identified problems. Engineering professionals can be understood to embody characteristics of engineering and its practice, including: an ability to visualise, think critically and systematically in identifying and deconstructing problems and forming creative and innovative solutions. Engineering can be understood as sharing some characteristics with other domains such as science, technology and mathematics with the nature of engineering as a practice presenting the opportunity to integrate insights of science, use of tools and technology and mathematics within engineering experiences. However, engineering must also be understood as distinct from these domains and considered as a singular domain with its own relationship to the UK and its population.

This synthesis of four approaches to defining engineering within the United Kingdom not only takes in consideration the common public and expert views of engineering but also considers the unclear relationship between engineering and other STEM domains. In considering the conceptualisations of engineering held by differing groups this definition acknowledges a socially constructed nature to meaning and its subjective interpretation. The cultural context of the engineering domain is also noted as influential in structuring a definition of engineering. Though not succinct, the developed definition offers a perspective that can aid in understanding the scope and nuance of the engineering domain and support the work of this thesis in understanding engineering within the UK context.

Engineering in the United Kingdom

Having defined the theoretical concept of 'engineering' it is next possible to explore how this domain is actualised within practices in the United Kingdom. A synthesis of literature drawing on historical and contemporary perspectives of engineering is necessary to understand the wider context in which engineering is perceived and interacted with in everyday lived experiences. This examination considers ongoing change facing the engineering domain and the resulting cultural, economic and educational positioning of engineering in the UK.

A Historical Perspective of UK Engineering

The philosopher Michel Foucault supported the value of historic perspectives noting that a 'history of the present' is a vital tool for understanding contemporary contexts (Garland, 2014). A historic perspective on engineering in the United Kingdom conveys a centuries-long narrative of industrial and technical heritage tied to a national identity as developers and exporters of world-changing innovation (Buchanan, 1985; Hudson & Hudson, 1989). It is notable that the practice of engineering on these shores predates the formation of the nation itself: historic records show the decisive impact of William the Conqueror's military engineers and prefabricated fortifications during the Norman Conquest centuries before the unification of England, Scotland, Wales and Northern Ireland (Smithers, 1998). Engineering would remain largely a military practice until the later part of the 18th Century when civilian or 'civil' engineering grew in prominence with the formation of the Society of Civil Engineers in 1771 and Institution of Civil Engineers in 1818 (Institution of Civil Engineers, 2022; Oxford DNB, 2022). This time saw rise of the Industrial Revolution, a period where engineering and its innovations directly reshaped the UK and its national culture and identity from agrarian to industrial, from rural to urban, and from cottage industry to high-volume manufacturing. The dramatic growth in productivity from these innovations led to a prominence and spread of engineering industrialisation across the globe (Griffin, 2018). This momentum of engineering innovations in the UK fuelled the later technological revolution in the late 19th and early 20th Centuries including innovations such as the steam train, television and computer that continue to shape the UK culture and society (Dillistone, 1956).

This very brief historic perspective demonstrates the significant influence of engineering on the structure and development of culture and society in the UK context. The dynamics of power as demonstrated by William the Conqueror's military engineers, the development of industry and decline of traditional social structures during the industrial revolution, or the value of specific innovations such as steam trains or early telecommunications in shaping the social landscape all demonstrate the influence of engineering on the development of the nation. It is notable that the UK not only adopted these innovations but was the place where many of these innovations were developed, rooting engineering innovation into the national identity of the United Kingdom. Engineering is not simply a set of occupations or practices but a deeply influential force acting on the UK and its population to shape identity, society and culture. This context of engineering must be considered: research that examines the engineering domain in a manner that neglects these deep cultural roots would likely result in an incomplete conceptualisation that is at odds with the objective of this thesis to develop greater understanding of engineering in the United Kingdom.

Engineering in the Modern United Kingdom

The significant influence of engineering identified in this historic perspective supports the need to understand engineering and its contemporary influence in the United Kingdom. A critical examination of engineering within the contemporary context reveals a dramatic shift in the place of engineering within UK society. Engineering practices were once highly visible and interacted with by individuals but in contemporary times might instead be characterised as 'hidden' and changed resulting in lesser comprehension of the domain.

Whilst engineering continued to play an influential role in the UK context throughout the first half of the 20th Century (including the dramatic period of the First and Second World Wars) by the end of the 20th Century the place of engineering within the UK culture and economy had changed. Manufacturing, once the dominant force of engineering within the UK, had dramatically diminished. The Gross Value Added (GVA: a measure of the proportion of GDP contributed by a sector or industry) for manufacturing fell from 30.1% in the 1970s to just 10% by the 2010s (EngineeringUK, 2018; Office for National Statistics, 2019). Where 29% of the population had been employed in manufacturing from 1948-1959 only 9% were in these roles by 2000-2016 (Office for National Statistics, 2019a). These rapid shifts in the dominant practice of engineering fundamentally challenged the place of engineering in the UK culture: engineering was now less visible in society with the loss of long-established practices and local identities for engineering. Vast proportions of the population no longer worked in manufacturing roles restricting the presence and visibility of manufacturing in the lives of many. This 'post-industrial transition' was a marked departure from centuries of entrenched engineering practice. Where the fifty-year window of 1770-1820 had seen the launch of the Industrial Revolution the fifty years of 1970-2020 saw its ebbing recession.

Following this transition from a goods-based to service-based economy engineering now holds a very different position in the UK economy: the number of manufacturing roles has diminished over 60% between 1979 and 2013 with a noted movement from manufacturing leavers into service roles (Hardie & Banks, 2014). This shift has seen a growing number of engineers occupying roles in non-engineering sectors and a decrease in the proportion of engineers in engineering sectors (EngineeringUK, 2022). This ongoing change is also demonstrated in the registration of new enterprises: from 2011 to 2016 the growth in manufacturing (+8.9%) was dramatically outperformed by almost all other engineering industries including information and communication (+40.8%), professional scientific and technical activities (+48.9%), administrative and support service activities (+48.9%) or electricity, gas, steam and air conditioning supply (+510.9%). In 2016 only 19.1% of engineering enterprises were registered as manufacturing compared to 29.2% in information and communications and 25.2% across multiple industrial categories (EngineeringUK, 2018). Manufacturing remains a significant engineering practice in the UK but is deeply changed with fewer individuals working in manufacturing roles and a very different practice than in previous decades (EngineeringUK, 2022). The future of manufacturing is predicted to continue this evolution with growing roles of automation, robotics, mechatronics and artificial intelligence further reshaping this practice (Institution of Mechanical Engineers, 2021).

Engineering remains a vital component of the UK economy contributing £420.5 billion (a quarter of the national GVA) in 2015 – more than the retail and wholesale, and financial and insurance sectors combined (EngineeringUK, 2018). However, engineering is no longer the homogenous, manufacturing-dominant practice it had previously embodied for centuries. In its place is a diverse and multifaceted domain with engineers acting out roles in many different sectors and contexts. This has shifted engineering from a singular, easy to comprehend practice to one with many dimensions. Engineers are now 'hidden' in many contexts working with increasingly digital, advanced or automated (and therefore, less publicly recognisable or comprehendible) practices such as telecommunications, biomedical engineering, green engineering or space/aerospace engineering. Demand for qualifications amongst engineers is now greater demonstrating the more sophisticated nature of these practices: where 26% of manufacturing was completed by those with no qualifications in 1993 this had dropped to just 8% by 2013 (Hardie & Banks, 2014). The idea of a labour intensive, manufacturing practice of 'dirty' engineering is now less valid and the identity and practices of modern engineers less easily comprehended. In comparison with the centuries-long history of largely static practices of engineering this change represents a colossal cultural shift in very recent memory.

The Ongoing Impacts of Change in UK Engineering

It is reasonable to question whether the shift from a simplistic structure of manufacturing-dominant engineering to a complex structure of varied and hidden engineering practices has impacted how engineering is perceived and experienced within UK culture and society. Little literature has studied this topic longitudinally necessitating a critical analysis of snapshot sources from recent decades to understand the impact of this change on the population and engineering domain. Examinations of public literacy for engineering support this assertion finding that the UK public have only a limited understanding of the engineering domain as would be expected given the now ‘hidden’ nature of engineering practices (Marshall et al., 2007; Institution of Mechanical Engineers, 2016; Institution of Mechanical Engineers, 2017). Critical analyses identify that the general public conceive of engineering as more blue-collar than white-collar, yet more ‘thinking’ than ‘manual’ suggesting a white-collar role but a blue-collar expectation of duties. This position is further supported by the identification that a large proportion (29%) of UK adults view engineering as a dying industry supporting the view that many still understand engineering in regards to manufacturing and its decline and are unaware of the hidden contemporary engineering domain that has taken its place (Castell et al., 2014; Institution of Mechanical Engineers, 2016). Collectively these findings suggest that a significant number of people within the UK still conceive of engineering according to its past structure as a goods-based practice. Worryingly, this is not only the case with older generations who may have first-hand experience with dated engineering practices but is also found amongst younger generations who are unlikely to have encountered these dated practices of engineering (Institution of Mechanical Engineers, 2017). Younger groups report a more ‘manual’ (as opposed to ‘thinking) understanding of engineering than adults (Marshall et al., 2007) and will often characterise engineering as a ‘dirty’, ‘too technical’ or ‘career for men’ (Bevins et al., 2005; EngineeringUK, 2019). Whilst it is difficult to track these characterisations over time due to differing samples and methodological approaches the presence of dated ideas is worrying: one study identified that a quarter of young people view engineering jobs as based in factories and half view these roles as taking place in dirty working environments (Ipsos Mori, 2001). Findings such as these imply that the dated conceptualisation of engineering as a dirty, manufacturing focused practice has perpetuated despite the engineering domain having evolved away from this practice over time.

The less positive attitudes and uninformed conceptualisations of young people are concerning given the recognition that attitudes held during formative years are instrumental in shaping later interests in study and careers (Archer et al., 2013; Institution of Mechanical Engineers, 2010; Woodward & Woodward, 1998). Young people report a lesser career interest in engineering (22.4% generally, but only 15.2% for manufacturing and production) compared to science and mathematics (33.1%), a lesser interest in learning about engineering (40.8%) compared to science (60.4%), technology (57.5%) or mathematics (53.1%) and think that engineering is generally less important (21.8%) than science (60.2%), design and technology (32.1%) or mathematics (55.9%) (Hutchinson & Bentley, 2011). The particularly poor career interest of young people for manufacturing (only 15.2% positive responses) highlights a lack of interest in engineering as it was previously practiced in the past. It may be that the engineering attitudes of young people are more positive towards a modern and accurate conceptualisation of engineering given its links to topics that young people care about such as technology and fighting climate change (Natural England, 2021). However, the conceptualisation of engineering amongst young learners is seemingly limited questioning the degree to which they might comprehend this connection. Regardless, the perpetuation of dated conceptualisations of engineering may play a role in the less positive engineering attitudes of young learners further demonstrating the danger of this confused, outdated or incomplete cultural conceptualisation of engineering.

The lingering presence of this limited, negative and dated conceptualisation of engineering and its perpetuation to younger generations may be understood through a consideration of informational sources which inform engineering concepts. Past literature acknowledges that adults and children develop their conceptualisations through differing strategies with younger generations developing their understanding of engineering from parents, school settings and through social media to a greater degree than adults who access this through lived experience and contact with engineers (Marshall et al., 2007; EngineeringUK, 2019; EngineeringUK, 2020). The sources drawn on by younger generations may themselves contain dated conceptualisations perpetuated through cultural ideas and human vectors. For example, media sources accessed by young learners are noted to convey engineering in unrealistic manners that poorly fit contemporary practices (Cheryan et al., 2015; Fabian, 2012).

The limited presence of engineering within UK school contexts likely worsens public comprehension of this domain. The UK features four devolved national structures to education making it difficult to generalise the educational experiences of learners across the UK. However, whilst engineering features somewhat more in the Scottish education system (and recent changes to the Welsh system may yet see engineering introduced to a greater degree) generally speaking the national curricula of the UK lack a strong, consistent and modern presence of engineering (Scottish Government, 2016; Welsh Government, 2020). Primary and secondary school curricula often do not prominently feature engineering, instead prioritising other STEM subjects such as science or mathematics (Council for the Curriculum Examinations and Assessment, 2007; Department for Education, 2013). For this reason, the UK education systems may be understood as embodying a ‘science first, engineering later’ structure with a foundation of highly prioritised science study intended to later provide access to engineering educational pathways. This relationship demonstrates an institutional link between the domains of science and engineering, but as outlined earlier in this chapter science and engineering cannot be considered to be identical questioning how directly a science dominant curriculum could support later engineering learning. It might be argued that the subjects of Design and Technology/Technologies represent a form of engineering learning within

UK primary and secondary schools. This is reasonable as the focus on making, design and technology within these curricula does align to the definition of engineering established in this thesis (Department for Education, 2013a; Scottish Government, 2022). However, the curricula for these subjects also often contain other forms of making or design including crafting, cooking or textiles which would not align with a contemporary understanding of engineering. This challenges the notion that Design and Technology/Technologies is truly representative of engineering. However, even if these subjects were acknowledged as a form of proto-engineering education the low status and priority of these subjects would question their impact on engineering comprehension: for example, the number of Design and Technology GCSE students has decreased by 53% from 2016 to 2022 (Education Datalab, 2022). Engineering features more prominently within Further and Higher education in the UK, however this presence may be considered too late to meaningfully impact wide scale comprehension for engineering given the lack of compulsory national curricula at these stages and the recognition that young learners align their interests and identity to subject areas at earlier ages (Archer et al., 2013; Institution of Mechanical Engineers, 2010; Woodward & Woodward, 1998).

As a result of these curricular structures most individuals experience little meaningful engineering learning within their education. If a national curriculum is thought of as a source of public literacy, then this goes some way to explain the limited and confused conceptualisations of engineering noted within literature. Teachers are also reportedly a prioritised source of information for young learners but are acknowledged to possess a low level of engineering knowledge and confidence answering engineering questions (EngineeringUK, 2020; Jones et al., 2021; Lewis et al., 2021). This limited knowledge and confidence is present even amongst STEM subject teachers. The limited engineering knowledge of teachers is unsurprising given the limited presence of engineering within initial teacher training, national curricula and limited understanding within society as a whole. It is not unreasonable to assume that in the absence of a full and contemporary understanding of engineering teachers may inadvertently draw from dated conceptualisations of engineering in their classrooms. Teachers may also draw from personal experiences of engineering from their own lives or youth and in so doing perpetuate dated or incomplete ideas of engineering. These limited concepts may be perpetuated to young learners actively (through dialogue) or inactively (through an inability to recognise and challenge misconceptions amongst learners) - if engineering is introduced in classroom settings at all (EngineeringUK, 2020). As a result, it is possible that an incomplete conceptualisation of engineering as a manual, dirty, male-only, factory manufacturing-based practice is perpetuated to younger generations in spite of a more modern, yet ‘hidden’, practice of engineering in the UK.

The UK’s Engineering Problem

In light of the outdated public understanding of engineering, low interest of young learners and limited presence of engineering in national curricula it is unsurprising that the United Kingdom faces entrenched challenges with its engineering domain. Two issues are particularly well-recognised as threats to the practice of engineering. First, a significant engineering skill supply issue is documented in the UK with an insufficient number of engineering-skilled individuals available to fill the demand for roles. Second, the supply of individuals who do become proficient in engineering is highly homogenous betraying an inequitable practice of UK engineering dominated by white, male and middle-class individuals. This second issue represents a social injustice and challenge to fairness within UK society. An examination of these issues within the UK context highlights their interconnectivity as two aspect of the same underlying problem and a need for greater insight to understand how young people are supported to become engineers given the cultural context of engineering in the UK.

The issue of inadequate engineering skills supply is long-recognised in the UK, featuring in government reports such as *Realising Our Potential* in 1993 (UK Government, 1993)*, Excellence and Opportunity* in 2000 (Department of Trade and Industry, 2000), *Professor John Perkin’s Review of Engineering Skills* in 2013 (Department for Business Innovation and Skills, 2013) and *Delivering STEM Skills for the Economy* in 2018 (House of Commons Committee of Public Accounts, 2018). This demand is recognised by engineering industries: 46% of employers surveyed in one study reported recruitment issues related to poor skill supply whilst a quarter of employers reported skill gaps in their organisations (The Institution of Engineering and Technology, 2017). Interventions have attempted to address this skill gap such as prioritised immigration of those possessing engineering skills (Migration Advisory Committee, 2008; 2010; 2020) or the introduction of new pathways to engineering skill development for workers and young learners (Department for Education, 2021; National Audit Office, 2018). However, despite these measures a skill gap continues to threaten the practice of engineering in the UK (The Institution of Engineering and Technology, 2021).

Projections of engineering skill demand have identified that each year from 2014 to 2024 the UK will require 124,000 new engineers and technicians for core engineering roles (roles that are entirely dependent on engineering expertise) and a further 79,000 individuals in related engineering roles (roles that require a mix of engineering and non-engineering expertise) (EngineeringUK, 2018). Of this annual demand for 203,000 engineering skilled individuals, 66,000 are required to be trained/educated to Level 3 and 137,000 to Level 4 standard in recognition that the UK workforce is expected to be increasingly higher skilled – by 2024 54.1% of the workforce are expected to possess Level 4 or above qualifications up 10% from 2014 (EngineeringUK, 2018). Over ten years this analysis estimates a demand for 2.3 million further engineering skilled individuals to fill both pre-existing roles that become vacated (replacement demand) as well as newly created roles that develop within the economy (expansion demand). An exploration of expansion demand confirms the earlier characterised changes to engineering underway in the UK with large decreases in the overall demand for manufacturing roles (-239,855 by 2024) (EngineeringUK, 2018). The characterised shift to a diverse, modern 'hidden' practice of engineering is also supported by expansion demand for roles in construction, information and communication, and professional scientific and technical activities. Projections identify expected shortfalls of 83,000-110,000 Level 3+ engineering-skilled individuals per year (EngineeringUK, 2018). Demand for engineering expertise in the UK is therefore high, increasing and changing over time to become more diverse in evolving engineering practices and sectors.

This demand for engineering skills would represent a significant challenge alone but is made more difficult by the further challenge of poor and inequitable participation with engineering education and careers which limits the supply of engineering skills. Limited and inequitable participation pervades the skill development pathways of engineering in the United Kingdom manifesting from the earliest opportunities for young learners to elect to participate in engineering education. In secondary education the number of learners in England, Wales and Northern Ireland who elect to study Design and Technology each year is low and decreasing: where 185,279 studied this programme in 2016 only 86,297 elected to study this subject in 2022 representing a 53% decline in six years. Not only is participation with this curricular representation of engineering in decline but participation is deeply inequitable with girls representing only 30% (N=25,589) of total students (N=86397) (Education Datalab, 2022). Whilst Design and Technology qualifications are not essential for later study or career access in engineering this skewed and limited participation with engineering learning demonstrates inequity at the first opportunity for learners to choose a trajectory towards or away from engineering/engineering-like education (Tuckett, 2022).

This trend of inequitable participation and representation continues in later stages of education. In 2020 only 1.7% of Further Education students in England studied A-Level Design and Technology and only 1.9% studied a Level 3 vocational engineering qualification (Tuckett, 2022). The trends of inequity are also noted in apprenticeship participation: of the 39,780 Intermediate, Advanced and Higher engineering apprenticeships started in 2018/19 by 16-18 year olds 94% (N=37,340) were started by male students compared to just 6% (N=2440) by females learners. Participation in these apprenticeships was also deeply skewed by ethnicity with those from white ethnic backgrounds (93%, N=37,110) overly represented compared to those from black (1%, N=480) or British Asian (2%, N=920) backgrounds (Department for Education, 2019). Unsurprisingly, this trend of inequity within engineering pathways continues into Higher Education: of the 124,095 first degree engineering and technology enrolments in 2019/20 81% (N=100,905) were male whilst only 19% (N=23,105) were female. Notably, of UK domiciled enrolments that year those from white groups were less represented (68%, N=62,370) compared to black (7%, N=6835) and British Asian (16%, N=15,120) groups demonstrating nuance and intersectionality within engineering inequities (HESA, 2022). These findings demonstrate deeply patterned access, participation and representation within UK engineering education.

The engineering inequities found within education are also, inevitably, found within patterns of progression from education into professional engineering contexts. In 2013/14 men found full-time engineering occupation employment in six months post-graduation more often (56.1%) than women (52.4%) (Royal Academy of Engineering, 2019). This pattern is maintained for ethnicity with white graduates reporting greater success (60.4%) than black (36.7%) or British Asian (40.9%) groups. These patterns are established across many years of graduates demonstrating entrenched patterns of inequity in ‘success’ following education which disproportionately benefit some groups over others (Royal Academy of Engineering, 2019). Unsurprisingly, the current UK engineering workforce also demonstrate significant patterned inequities. Only 16.5% of those in engineering occupations are female, only 11.4% come from non-white ethnic groups and there is a documented skew towards greater representation by those with more privileged backgrounds (EngineeringUK, 2022). This collation of findings demonstrates a deeply patterned participation with engineering in the UK originating from early education and enduring throughout educational pathways into engineering careers. Engineering inequities are noted to affect the access, participation, representation and success of individuals within the UK leading to a highly homogenous population of engineers.

The pervasiveness of this pattern and its lack of context-dependency in the engineering domain imply that the origin of these inequities lie in the ideas, customs and social behaviour of the nation – in other words, the foundational culture of UK society. This assessment is supported in several ways. First, a cultural perpetuation of engineering inequity is consistent with the cultural perpetuation of dated conceptualisations of engineering to younger generations outlined earlier in this chapter. Second, engineering inequities are not a contemporary or context-dependent/situational issue but one that is long recognised and contended with throughout the UK. The enduring nature of engineering inequities implies that these patterns are entrenched in a foundational characteristic of the national context that is present throughout time and place such as the omnipresent influence of a national culture. Finally, the resistance of these inequities to intervention despite decades of attention and more than one billion pounds of investment offers further evidence that the root origin of these inequities lies deeply within the enduring cultural context and identity of the UK in a manner that is difficult to change (National Audit Office, 2018).

The significance of culture to engineering inequities is further supported by the ubiquity and diversity of forms these inequities take within the UK context. Gender inequities are associated with inequitable understanding of engineering (25% of boys in one study report knowing a lot of engineering, compared to 8% of girls), a greater awareness of engineering applications in the real world and the capacity to recognise engineering in curricula learning experiences (Institution of Mechanical Engineers, 2017). Boys also report a greater aspiration to engineering employment (42.9%, compared to 7.6% of girls) as well as slightly greater participation in engineering clubs/school activities (7.7%, compared to 5.0% of girls) (Hutchinson & Bentley, 2011). Despite a low representation in engineering industry and lesser post-graduate progression rate Black and Minority Ethnic (BAME) learners report slightly greater participation with engineering clubs/school activities (8.4%, compared to white learners 5.6%) (Hutchinson & Bentley, 2011), with British Asian learners possessing a greater aspiration to engineering careers and identification as an ‘engineering type person’ than other ethnic groups (EngineeringUK, 2022a). The identification that ethnicity and gender effects intersect and that home/parental influence is associated with inequities in engineering further demonstrate the complexity and cultural nuance within inequities in the engineering domain (EngineeringUK, 2022a; MacDonald, 2014). These examples demonstrate that the inequities of engineering are not solely related to education or career participation but are fundamental to the lived experience of these groups and can manifest in many group distinctions. This supports the notion that these inequities are entrenched within the culture of the UK society rather than relegated to a particular context or situational expression.

The longstanding and pervasive role of these problems arguably represents the most important challenge facing the UK engineering domain. A continuation of high demand but low supply of skills that unfairly excludes groups of individuals is a threat to the UK and its engineering domain. Economic problems relating to skills supply and demand or social justice problems of fairness in access and representation within the desirable engineering domain can be understood as symptoms stemming from the same underlying issue of engineering inequities determining restricted access for some groups to the engineering domain. A sophisticated understanding is necessary to examine and challenge these inequities. Some degree of understanding has been developed within current literature such as who is favoured more (white, middle class males) or less (women, BAME groups, those with less privileged backgrounds) or how these groups view the engineering domain.

However, the continuing presence of engineering inequities despite this learning clearly articulates a need for a more sophisticated understanding and intervention. In particular, this development of understanding must address the fundamental roots of this inequity within the UK context. Conceptualisations of inequity based on group characteristics such as gender or social class may act as useful key performance indicators of progress but cannot by themselves indicate the deeper characteristics underlying these inequities. An understanding of who is represented within the engineering domain is not the same as understanding the mechanics through which inequity is shaped and perpetuated. Inequities must also be recognised as complex and intersectional: an interpretative lens that artificially siloes gender, social class or ethnicity cannot account for underlying nuances and interactions between these characteristics within engineering inequity. An understanding centred on these fixed or relatively fixed group characteristics of gender, social class and ethnicity is also unhelpful in informing interventions to challenge inequity. An understanding that girls are underrepresented in engineering does not directly inform effective interventions to address the underlying causes of this patterned access. Further research is necessary to identify deeper issues or strategies to overcome this issue. Therefore, a lens of inequity that is overly reductive can be argued as unlikely to offer sufficient insight to effectively overcome these inequities. Little research has adopted a complex, intersectional and practically-oriented perspective on engineering inequity within the UK context. More research has historically considered inequities in the science domain but this body of research has, until relatively recently, largely focused on gender and neglected the consideration of race or intersectionality (Cabinet Office, 2017; Commission on Race and Ethnic Disparity, 2021; Roberts, 2002). If little deeper consideration of inequity is present within the more often studied science domain then it is unsurprising that very little study of engineering inequities has taken place. The enduring nature of engineering inequities in the UK demand the development of sophisticated, novel and solution-orientated understandings of how to encourage a diverse and growing population of future engineers.

Conclusions

In this chapter the engineering domain of the United Kingdom was explored to contextualise the problematic engineering inequities that are central to this thesis investigation. A definition of engineering was established that recognised the varied and socially constructed nature of engineering conceptualisations within the United Kingdom. A critical reflection on the historic and contemporary practices of engineering highlighted that engineering is now more hidden and less recognisable within the lived experience of the population. This analysis demonstrated the significance of cultural and social relationships with engineering and the importance of such considerations in richly contextualising the engineering domain. Engineering inequities were also critically explored as entrenched challenges that threaten the participation and diversity of coming generations of UK engineers. A critical synthesis of perspectives positioned skill shortages and a lack of diversity in UK engineering as two aspects of the same underlying problem in how people are supported to become engineers. The persistence of these challenges is recognised as a threat to resilience of the nation and the social justice and fairness of UK society. These inequities were reasoned to persist, in part, due to dated cultural concepts of engineering, the restricted presence of engineering in the education system, and a limited understanding of how engineering inequities develop and perpetuate to young learners. It was reasoned that current understandings of engineering inequity are limited and that greater insight into the underlying mechanics of inequity are necessary if interventions are to successfully address social injustice and economic challenges within the UK engineering domain.. The objective of this thesis is therefore established: to develop a more sophisticated understanding of engineering inequities in the United Kingdom with a particular focus on how young learners – representing the next generation of engineers - may be supported for greater access, participation, success and representation with engineering.

CHAPTER TWO: FINDING ENGINEERING IN SCIENCE CAPITAL

Introduction

The first chapter of this thesis acknowledged that the United Kingdom faces deeply entrenched inequities of access, participation, success and representation with its engineering domain. These inequities were framed as resistant to change, rooted within the social and cultural context of the nation, and a threat to the development of young learners as future engineers. A need to develop a more sophisticated understanding of these inequities was identified and adopted as the objective of this thesis to better support interventions to grow and diversify next generations of engineers. In Chapter Two, the adoption of a popular model of science inequity is critically considered to support this objective. The 'science capital' model is recognised as a deeply insightful and novel perspective of science inequity that supports greater understanding and intervention to promote science equity amongst young learners. The underpinning cultural and social framework of this model and its focus on developing sophisticated insights into inequity within a STEM domain align to the objective of this thesis and support the potential adoption of this model. However, the definition of engineering introduced within Chapter One established a complicated relationship between the domains of engineering and science necessitating a confirmation that the science capital model will apply to the engineering domain. To do this the theoretical model of science capital is critically explored to determine the value of this perspective to issues of engineering inequity. This judgement will determine the adoption of the science capital perspective within this thesis to better understand and address engineering inequities in the UK.

Science Capital and STEM

As acknowledged in Chapter One, the relationship between engineering and science can be understood as a positional, family resemblance with the degree to which these domains overlap dependent on the position from which this comparison is made (Wittgenstein, 2010). One commonality that all STEM subjects share to some degree is the issue of entrenched and resistant inequities which affect access, participation, representation or success in these domains (APPG on Diversity and Inclusion in STEM, 2021). It has long been recognised that some groups are much more likely than others to engage with educational and career pathways in STEM (Bosworth et al., 2013; Codiroli-McMaster, 2017; Smith, 2011). The social justice and economic health implications of these entrenched inequities have prompted a variety of novel perspectives and approaches to investigate these concerns (APPG on Diversity and Inclusion in STEM, 2021; Archer et al., 2020; National Audit Office, 2018). A growing body of research literature has provided insight as to the patterns of inequity found within the UK context and internationally (Dawson, 2019; Emsi, 2018; Jones et al., 2021). Arguably the most notable and valuable body of such research in recent times is the model of 'science capital' developed by Louise Archer and colleagues to explore science participation and inequity in the UK context. First published in 2014, this model unified previous lines of inquiry under a new theoretical perspective to produce a novel understanding of how young people come to interact with science. This model is particularly concerned with social injustices in aspirations for science: who is supported to aspire to future educational and career pathways for science in recognition that such aspirations differ between social groups in an inequitable manner (Archer et al., 2015). Since its inception the science capital model has become widely adopted featuring in international research, practical interventions and government monitoring (Department for Business, Energy, & Industrial Strategy, 2020; Du & Wong, 2019; Godec et al., 2017).

Archer and colleagues adopt the capital framework of Pierre Bourdieu: a conceptual framework of thinking tools developed to conceptualise social class reproduction, the nature of group differences and the perpetuation of identity and societal structure across generations (Bourdieu & Passeron, 1977). Within this perspective 'capital' is seen as the assets or resources which govern social reproduction, acting as legitimate, valuable, transferable resources that bring advantage to the possessor in certain contexts. The collective capital an individual possesses, Bourdieu argued, is used socially to determine an individual's cultural competence - and so, their social standing/class (Bourdieu, 1984). In this way capital represents not only how well supported an individual is to engage within a context, but how that individual is socially identified. Bourdieu offers this view of capital as tool for understanding distinctions between groups, innovating on earlier work on the capital perspective by moving beyond an exclusively economic structure of capital to also include capitals that were social or cultural in nature (Bourdieu, 1986; Marx & Levitsky, 1965). Cultural capitals were framed by Bourdieu as 'cultural goods' that develop over time and might include tastes, knowledge, skills, credentials, or possessions. These resources may be embodied (internalised within the self), objectified (owned as material property), or institutional (formally certified and recognised qualities) in nature (Bourdieu, 1984). Social capitals were defined as the forms of capital available to an individual through their social network (Bourdieu, 1986). The capital an individual possesses, paired with their habitus (socialised development in early age leading to dispositions that guide action and reaction – a personal social blueprint developed through mimesis) and the field context they find themselves in shapes the human social environment.

Bourdieu’s work was broadly concerned with artistic forms of capital – with artistic taste, dispositions and capital framed as distinguishing social class. The value of certain capitals is positioned as arbitrary and decided by those with greater power in society – in this way the powerful maintain the value of their own assets and minimise the assets of others to maintain the status quo of social structure (Bourdieu, 1986). The argument that those with greater capital possess greater social standing implicitly positions aspects of ‘deficit thinking’ within the Bourdieuian perspective. Deficit models of thinking argue that the root cause of an issue is a deficit of some quality or characteristic amongst a disadvantaged group (Smit, 2012).For example, in a classroom setting a deficit model of learning may position a lack of motivation or effort as the cause of poor exam performance. In contemporary times such deficit models of thinking are criticised as oversimplistic and neglectful of positive interpretations of individual differences. Whilst Bourdieu does recognise that a deficit of capital is disadvantageous his perspective also recognises that the valuation of capital is arbitrary and that the distribution of capital that leads to deficits amongst some is a consequence of power dynamics in society and not individual shortfalls. In this way Bourdieu’s perspective may be understood as a deficit model of thinking that does not attribute blame or responsibility on an individual. The capital framework also avoids deficit model criticisms of oversimplification through the adoption of further concepts such as habitus and field.

Archer and colleagues adopt Bourdieu’s perspective on socially determined societal structure into their own conceptual framework acknowledging the influence of cultural and social capital on group distinctions in science. In the case of science capital, Archer et al. consider both how science capital wields influence in society’s power structure (arguing that in the modern world knowledge and participation with science is valued in the same manner that Bourdieu argued high art is valued) but also shapes individuals in their trajectory for science (by positioning the possession of science capital as beneficial for later participation with science, and so, shaping patterns of inequity) (Archer et al., 2015). In this way the capital lens is adopted to provide insight into the social and cultural mechanics of science inequity.

Through this lens Archer et al. form a deep perspective on science inequity which can consider how resources for science are differentially distributed. This facilitates both an understanding of the ‘science haves’ and ‘science have nots’ of society, but also provides insight into the beneficial effects of capital in a manner that can support intervention. This adaption of Bourdieu is introduced by Archer et al. as a “useful augmentation of existing Bourdieuian conceptualisation of capital” which has been “absent or marginal within most Bourdieuian conceptualisations of capital” (Archer et al., 2015, p923).

Archer et al.’s use of the Bourdieuian framework in the development of the science capital model may be characterised as a practical adoption of this broad and sociological perspective motivated by a social justice philosophy. Archer et al.’s (2015) formation of this model is concerned with measurement and classification of individuals based on measurement of science capital ‘scores’ in quantitative terms. This purposeful approach facilitated the development of both a theoretical model and empirical instrument of science capital that could categorise individuals in terms of their possession of supportive resources for science. However, this is perhaps at odds with more popular theoretical uses of the Bourdieuian perspective in philosophical or sociological examinations of group differences. Further to this, whilst Bourdieu understood capital as more resistant to change in the ‘social reproduction’ of social class; Archer and colleagues instead implicitly consider the possession of capital as changeable with a more optimistic approach that intervention may lead to change in science trajectory (Archer et al., 2015; Bourdieu et al., 1977; Bourdieu, 1984; King et al., 2015). This adoption also distances itself from deficit thinking: whilst Archer et al. acknowledge group differences in the distribution of capital these differences are not positioned as a failing of individuals but a consequence of the wider societal structure surrounding science inequity. This is consistent with the broader social justice motivations of Archer et al.’s work. For these reasons Archer et al.’s (2015) adoption of Bourdieuian thinking must therefore be acknowledged as a more contemporary, if not quite radical, framing in line with adoptions by Yosso (2005) or Prieur and Savage (2013).

Archer et al.’s model of science capital includes a range of subcomponents which each, individually, are recognised in past research as important sources of influence for science identity or participation. These include subcomponents such as ‘scientific literacy’, ‘scientific-related dispositions/preferences’, ‘talking to others about science’, and ‘consumption of science-related media’ (Archer et al., 2012; Claussen & Osborne, 2013; Ho, 2010; Israel et al., 2001; Lyons, 2006). Not all subcomponents relate directly to forms of cultural or social capital with some instead representing activities and contexts where cultural or social capital for science may be obtained. For example, the inclusion of ‘out-of-school learning contexts for science’ is rationalised as a participation with contexts such as science museums in which science cultural capital such as scientific literacy may be acquired. The science capital model must therefore be understood as a construct: an aggregate array of ways in which proximity to the science domain is distinguished between groups and individuals in UK society and not strictly or simplistically a checklist for science resources. It should not be considered – nor does it claim to be – a total measure or complete framing of all science resources (Archer et al., 2015). However, in uniting past research findings into a single framing it does produce a novel conceptualisation of science inequity in the UK and in adopting the

Bourdieuian perspective can relate science participation to the wider societal structure and its social reproduction.

Drawing on this theoretical model Archer et al. (2015) developed a robust, reliability and validity tested empirical instrument to measure science capital amongst secondary school-aged learners (Archer et al., 2015). This development facilitated large scale investigations of science capital in the UK context that offered a wealth of insights demonstrating its novel value (Archer et al., 2015; DeWitt et al., 2016; Moote et al., 2021). Measurements of science capital amongst UK secondary school students found that only 5% of this population possess a 'high' level of science capital indicating that only a small proportion of this population are broadly supported with resources that support future involvement with science (Archer et al., 2015). Crucially, science capital scores were found to differ between social groups validating the relevance of this perspective as a lens for science inequity and its utility in distinguishing groups in relation to science trajectory. The results provided by the science capital instrument were found to align with existing understandings of who are or are not supported to engage with science, such as the recognition that boys and those from South Asian ethnic groups were better supported for science (Archer et al., 2015; Archer et al., 2013; Direito et al., 2017; Lyons, 2006). Novel insights into science inequity were also provided through this instrument such as the recognition that those in high science academic sets possess greater science capital or the identification of intersectional dynamics within science inequities (Archer et al., 2015). These findings demonstrate the value of the science capital model in efforts to understand and address group differences in science participation and highlights the value of a capital-based perspective on science inequity. This capital structure is inherently proactive as it suggests the forms of resource that are absent and that may be supplied to address inequities thereby supporting the design of interventions to address science inequity.

Science capital has been adopted by other researchers to support their investigations of science participation, pedagogy and equity (Canovan & Fallon, 2021; Hall et al., 2021; Ong et al., 2018; Padwick et al., 2015). The approach has been adopted overseas - despite its focus on the UK cultural context which might suggest that the specific model of science capital produced by Archer et al. is exclusively applicable to the UK (Cooper & Berry, 2020; Jones et al., 2021; Wilson-Lopez et al., 2017). Science capital has also been adopted institutionally in the UK featuring in the UK Government-led *Public Attitudes to Science* survey which explores how the UK public perceive and experience science to inform government policy and national decision making (Department for Business, Energy, & Industrial Strategy, 2020). The insights from the science capital perspective have been integrated into a pedagogical practice titled the *Science*

Capital Teaching Approach (Godec et al., 2017; King et al., 2015). This pedagogy focuses on introducing the concept of science capital to teachers as a tool for their thinking and supporting change to classroom practices to support students in a capital-conscious way. The uses of science capital can be seen as broad and legitimised within the UK and overseas, with a clear value for understanding and addressing inequity in both policy and educational contexts.

Science Capital and Engineering

The science capital model can therefore be understood as an innovative and nuanced perspective on science inequity that is sensitive to the cultural context and socially constructed meaning through its Bourdieuian framework, and practically oriented to developing understanding to address inequity. These virtues align the characterisation of engineering inequity outlined in Chapter One suggesting that the science capital model may offer value if adopted in this thesis to better understand engineering inequities in the UK. This adoption would represent a novel application of the model which has not previously been utilised to explore engineering inequity in great detail. However, as also noted in Chapter One, the domains of science and engineering are related but not identical questioning the direct relevance of science capital to the engineering domain. Past literature does feature such abstractions of science capital to STEM domains but none has first robustly validated this adoption as valid or effective (EngineeringUK, 2020a; Institution of Mechanical Engineers, 2014). If the generalisation of science capital to the engineering domain is not warranted then an adoption of science capital within this thesis would hinder efforts to build greater understanding of engineering inequities. It is therefore first necessary to validate the relevance of science capital to the engineering domain. Previous study of science capital has identified that the model outperformed a more general cultural capital model in efforts to understand science inequity (DeWitt et al., 2016). These findings suggest that a subject-specific approach to inequity is more impactful than a subject generalising approach when utilising the Bourdieuian perspective. This finding further supports the need to investigate to what degree engineering fits within the science capital model to determine whether this tool is suitably focused to understand the engineering domain.

An examination of science capital literature shows little explicit framing of engineering within the model: the term “engineering” is not used in Archer et al.’s early publications on the concept although “STEM” is used in wider discussions of science generally. Science capital is positioned as an evolution of Bourdieu’s arts-based model of capital, in this sense using science in a non-specific, ‘not-arts’ framing which it could be argued is generalisable to STEM and thereby inclusive of engineering. Yet in the empirical investigation of science capital, the framing of science is seemingly siloed to how science is seen in the UK educational curricula – distinct from technology, engineering or mathematics. These other STEM subjects are not empirically investigated directly or indirectly in the science capital methodology (Archer et al., 2015; DeWitt et al., 2016). This absence would later be confirmed with empirical findings from within the science capital literature suggesting that secondary school-aged participants consider 'science' to mean biology, chemistry and physics (and not the STEM subjects of technology, engineering or mathematics) questioning the degree to which engineering is implicitly included in this research if not mentioned explicitly in the framing used by Archer and colleagues (Moote et al., 2021). From a social constructionist perspective, the 'science' in 'science capital' is therefore not inclusive of engineering regardless of the intention of its creators. Seemingly then, science capital relates to subjects that are within the UK science curricula, however as outlined in Chapter One engineering is distinctly underrepresented in this context implying that engineering is also inherently absent from the science capital model.

The underlying Bourdieuian conceptual framework utilised by Archer et al. (2015) would also support the premise that engineering cannot be effectively considered within the science capital model. As noted in Chapter One the domains of engineering and science are not identical and can be understood as distinct from certain positions. For example: engineering is not very present within the UK national curricula whereas science is a high priority subject area throughout compulsory education; the general public have a much greater level of interest and understanding of science than they do of engineering (Castell et al., 2014; EngineeringUK, 2018; Institution of Mechanical Engineers, 2016; Institution of Mechanical Engineers, 2017; Marshall et al., 2007); and the exact patterns of inequity in the two domains can differ (WISE, 2014). These cultural distinctions are critically important under a Bourdieuian framework given its dependence on cultural components and sensitivity to cultural nuance (Bourdieu & Passeron, 1977; EngineeringUK, 2019). Differences in public literacy, presence in national curricula, and patterns of inequity for science and engineering would support the premise that science and engineering hold different relationships to capital in the UK, questioning the direct relevance of the science capital model to the engineering domain (EngineeringUK, 2020; MacDonald, 2014; Marshall et al., 2007). A lack of explicit navigation of this cultural nuance in the science capital literature suggests that science capital is not consciously framed to include engineering.

Despite this, research conducted by Archer and colleagues has empirically investigated the relationship between science capital and STEM and concluded that the model is to some degree related to engineering. Moote et al.'s (2020) paper found positive correlations between science capital and attitudes to science (r=0.779), technology (r=0.327), engineering (r=0.423) and mathematics (r=0.414) with the authors concluding that to a certain degree ‘science capital’ can be considered ‘STEM capital’ and so apply to engineering. However, this conclusion must be questioned noting the weak nature of these relationships between science capital and technology, engineering and mathematics. The relationship between science capital and science (r=0.779) is much greater than that between science capital and engineering (r=0.423) which highlights a very different relationship between science capital and these two domains. This challenges the notion that science capital will apply to the engineering context as effectively as it does to science. Further, as attitudes to science are themselves a subcomponent of science capital (scientific dispositions/preferences) it is unsurprising that a correlational analysis identifies a strong association between science capital and a measurement of science attitudes as in Moote et al.’s (2020) paper. The lack of a strong association between science capital and engineering attitudes in effect demonstrates that science attitudes and engineering attitudes are not the same – inherently validating the position that science capital cannot be considered as ‘STEM capital’ due to the differences within domains in this grouping. This further questions the wisdom of utilising science capital to understand engineering inequities. Clearly some degree of overlap or shared qualities are present to support a weak association between engineering and science capital (r=0.423) but this likely speaks more to shared similarities within the ‘family resemblance’ of STEM. However, as noted in Chapter One, this cannot be considered as a valid reason to assume equivalence between these domains (Wittgenstein, 2010). The fact that Moote et al.’s (2020) correlations are not all equal demonstrates that science capital relates to STEM subjects differently in the favour of science and detriment of technology, engineering and mathematics.

This same paper, Moote et al. (2020), provides further insight into the distinctiveness of engineering amongst the STEM grouping in the context of young people in the UK. This study deployed an identically worded measurement of STEM attitudes to 7,013 secondary school-aged participants and found that the mean score for engineering attitudes (8.75 out of 15) was much lower than those for science, technology and mathematics (10.19, 10.15, and 10.40 out of 15 respectively). This less positive attitude towards engineering compared to science is validated in further literature examining UK young people (Hutchinson & Bentley, 2011). Given that attitudes are a central element of the science capital construct this further suggests that engineering may be distinct from science in terms of capital. These findings demonstrate the outlying nature of engineering amongst the STEM grouping for young people in the UK. This may be due to the lesser presence of engineering in the national curricula compared with the remaining three subjects, but regardless of cause demonstrates the risk of equating ‘engineering’ with ‘science’ and thus further shows that engineering warrants its own examination.

This synthesis of evidence would indicate that science capital model may not relate to the engineering domain in a meaningful manner. Previous studies that have considered the link between science capital and engineering have done so in only a superficial manner and with findings that are questionably reliable due to methodological limitations.

However, as established in Chapter One, science and engineering share a complicated dynamic. This thesis recognises a relational aspect of defining engineering and its potential for overlap with the concept of science. A 'family resemblance' is identified with the potential for science and engineering to share common traits. This would add wariness to an assessment of science capital that does not appropriately approach this model in a granular fashion and consider its underlying characteristics. It is important to note that science capital is a construct of many different subcomponents: it is possible that some are relevant to engineering whilst others are not. For example, it may be that the forms of knowledge included within the 'scientific literacy' subcomponent align to knowledge used within the engineering domain. Whilst this may be true it could also be accurate to argue that 'symbolic knowledge of the transferability of science qualifications' is of lesser value to supporting future engineers due to the distinction of engineering professional qualifications.

To comprehensively understand the relationship between science capital and engineering we must also 'deconstruct the construct' and explore the underlying relationship between science capital and engineering.

If this model is found, as suggested, to not be theoretically inclusive of engineering then this would rule out the adoption of science capital within this thesis to understand and address engineering inequity in the UK. However, in completing this critical examination a more appropriate engineering-specific approach may be uncovered. In the following sections of this chapter the theoretical model of science capital will be explored in detail. Each subcomponent will be critically analysed and related to wider literature to determine the degree to which this construct can relate to engineering. The product of this analysis will provide a novel insight into the scope of science capital and its potential use in this thesis to explore engineering inequity in the UK.

Finding Engineering in Science Capital

Very little research literature has critically examined the theoretical model of science capital however, this theoretical structure is of great significance to the resulting practical tools now widely applied in the UK to understand science inequity. As a result, to meaningfully consider the degree to which engineering features within the science capital model it is necessary to deconstruct the science capital model to its foundational subcomponents.

The theoretical model of science capital consists of seven subcomponents. Of these, three are forms of cultural capital (scientific literacy, scientific-related dispositions/preferences, symbolic knowledge about the transferability of science in the labour market), two are forms of social capital (knowing someone who works in a science job, talking to others about science) and two are aspects of behaviours and practices where capital may be acquired (consumption of science-related media, and participation in out-of-school science learning contexts) (Archer et al., 2015). Considering the science capital model in this manner, as a collective of subcomponents, highlights the artificial nature of science capital as a construct. Science capital is a tool created to ease comprehension of science inequity which may be drawn on by practitioners, educators and policy makers to combat inequity. These science capital subcomponents are vital, interconnected aspects of science capital that are established in past literature as influential towards science aspiration. The subcomponents can be independently examined to uncover the underlying links between science capital and engineering.

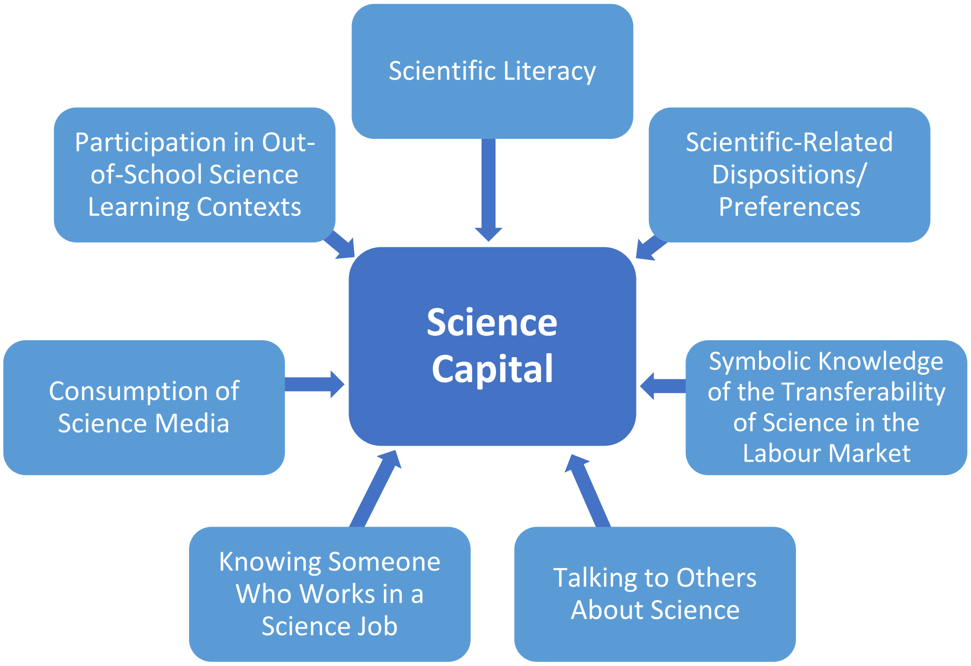

Figure 2.01 Archer et al.'s (2015) model of science capital with seven subcomponents.

<u>Scientific Literacy</u>

The first subcomponent of Archer et al.'s theoretical model is 'scientific literacy' defined as "scientific knowledge, skills and an understanding of how science 'works' and the ability to use and apply these capabilities for personal and social benefit” (Archer et al., 2015, p929). This form of cultural capital is framed as “vital” in considering cultural capitals for science, with the ways of thinking and acting, or ‘habits of mind’, of science positioned as central to a sense of scientific literacy (Claussen & Osborne, 2013). Several scientific habits of mind are explicitly identified as key to scientific literacy, including critical or analytical use of logic, identification of variables and numerical skills with data (Archer et al., 2015). This framing of scientific literacy is comprehensive, extending beyond the conceptualisation of literacy as simply factual knowledge to also consider the deeper embodiment of what it means to be literate in a topic, in this case a knowledge of scientific methods and ways of embodying the characteristics of someone involved with science.

Engineering is not explicitly mentioned in this outline necessitating a critical examination of how engineering fits within the scientific literacy subcomponent. Given the centrality of habits of mind to Archer et al.’s positioning of scientific literacy it is possible to consider whether the subcomponent is inclusive of habits of mind for engineering. Several published models of engineering habits of mind would suggest this is not the case. Previous research into engineering habits of mind has identified habits such as ‘systems thinking, creativity, communication and collaboration’ (Katehi et al., 2009), ‘problem finding, visualising, improving, adaptability, and creative problem solving’ (Lucas & Hanson, 2016), and ‘systems thinking, creativity, communication, optimism, optimization, and iteration’ (Huffman et al., 2018). These differ from habits of mind for science identified by various authors such as ‘scepticism, rationality, objectivity and curiosity’ (Çalik & Coll, 2012), ‘understanding peer review, scientific ethics and acknowledging uncertainty’ (Collins & Pinch, 1993) or those explicitly referred to by Archer et al. (2015), from Claussen and Osborne (2013), ‘patterns in data, numerical fluency, and deductive reasoning’.

The distinctiveness of these habits of mind for science and engineering align with the position of this thesis, as outlined in defining engineering in Chapter One, that the two subjects appear superficially similar but can be distinguished when more rigorously examined with a positional perspective. This supports the conclusion that engineering habits of mind – and therefore literacy in Archer et al.’s (2015) framing – is not included in the ‘scientific literacy’ subcomponent. Given Archer et al.’s adoption of habits of mind as key to literacy and the distinctiveness of habits of mind for science and engineering, we cannot consider the science capital literacy subcomponent to be inclusive of engineering in the framing established by Archer and colleagues. This conclusion is supported by wider models of engineering literacy by Huffman et al. (2018) and Chae et al. (2010) that recognise many dimensions of engineering literacy none of which are meaningfully represented within Archer et al.’s (2015) ‘scientific literacy’ subcomponent. Overall, this analysis would challenge the notion that scientific literacy as framed by Archer et al. is inclusive of engineering – either in relation to the habits of mind central to their framing or in relation to wider theories of engineering literacy. If this key subcomponent is not inclusive of engineering, this would suggest a fundamental lack of presence of engineering within the science capital model.

Scientific-Related Dispositions/Preferences

The second subcomponent of Archer et al.'s theoretical model of science capital is 'scientific-related dispositions/preferences'. No explicit definition of this subcomponent is given, though an example is outlined ("valuing of science in society" (Archer et al., 2015, p929)) and examination of the empirical instruments of science capital highlight that this subcomponent relates to attitudes of parents and young people, including interest in science and sense that science is important. Within the Bourdieuian framework, dispositions are closely linked to the concept of 'habitus' and play a role in propagating inequity across generations. For Bourdieu, habitus is an acquired and socialised set of characteristics which "generates perceptions, appreciations and practices" (Maton, 2014). Bourdieu reasoned that these dispositions are both 'structured' i.e., acquired through past experience, but also 'structuring' in that they shape the present and future through a developed set of "predisposition, tendency, propensity or inclination" (Bourdieu, 1977, p214). Parents are a key source of this habitus leading to the noted intergenerational endurance of group characteristics. Bennett et al.'s (2019) replicative study of Bourdieuian capital within the UK confirmed the continuing relevance of habitus as a tool to understand contemporary groups.

It might then be inferred that the 'scientific-related dispositions/preferences' subcomponent refers to the structured and structuring influence on an individual in relation to their scientific 'taste' including their tendencies, propensities and inclinations for science. This can be seen as attitudinal in nature relating to the attitudes of young learners, but in acknowledging the 'structured' influence of past experiences and socialised learning also considers parental attitudes as a source of habitus. Considering the science capital model is interested in trajectory towards science this consideration of parental influence is validated by White and Harrison (2012) who identify the influence of parents on educational and career choices of young people.

Having established this understanding of the subcomponent it is next possible to consider whether this subcomponent is inclusive of engineering. It is well established that differences can exist between interest and value judgements for different scientific domains, e.g. physics, biology and chemistry (Jones et al., 2000). This recognises that the concept of 'science' itself is a construct, often viewed as meaning 'biology, chemistry and physics' which might otherwise be seen as a collection of subjects much like the STEM grouping (Moote et al., 2021). Dispositions/preferences for science then are likely more multidimensional than suggested in Archer et al.'s subcomponent where science is described as a unidimensional catch-all, presumably meaning biology, chemistry and physics though this is not explicitly stated. This questions the validity of how the dispositions/preferences subcomponent is framed for science given noted variability in interest and valuing of biology, chemistry and physics. This also challenges the notion that science capital or 'STEM capital' could effectively bridge the differences in science and engineering and retain its specificity as a subcomponent.

The distinctiveness of dispositions for science and engineering in the UK would be confirmed by data from the 2019 Engineering Brand Monitor which shows that young people in the UK possess dispositions that are more positive about science (63%) than engineering (50%) generally, and more positive about science jobs (49%) than engineering jobs (41%) (EngineeringUK, 2019). This distinctiveness in dispositions for engineering is confirmed by Hutchinson and Bentley (2011) who established that dispositions of enjoyability, importance, utility and personal confidence amongst secondary school-aged learners all differed for science and engineering, with engineering dispositions less positive than those for science. Critically, some of the dispositions considered within Hutchinson and Bentley's study are also the dispositions considered within the science capital model (interest, utility, importance) directly questioning the degree to which Archer et al.'s subcomponent can be presumed to apply to engineering. To assume that this subcomponent is inclusive of engineering would overestimate the positivity of dispositions for engineering.

The distinctiveness of dispositions for science and engineering are also noted amongst parents and adults in the UK, questioning the validity of the assuming that the science capital subcomponent is inclusive of engineering. Parents are less confident talking about engineering than science (EngineeringUK, 2019) and adults in the UK also find engineering to be less interesting than science (Department for Business, Energy, and Industrial Strategy, 2020). Given the importance of family influence on habitus, and the development of dispositions within young people, this would further support that dispositions for science and engineering differ in the UK and that the scientific dispositions subcomponent cannot reasonably be assumed to access engineering dispositions.

Symbolic Knowledge of the Transferability of Science in the Labour Market

The final cultural capital subcomponent within the science capital model is ‘symbolic knowledge of the transferability of science in the labour market’ which is defined as an appreciation that science qualifications are valuable and transfer a benefit in the context of the labour market. This subcomponent is therefore concerned with the knowledge of how to approach and navigate through educational pathways towards valuable qualifications which Archer et al. refer to as “a particular form of symbolic scientific cultural capital... related to differential patterns of aspiration” (Archer et al., 2015, p930) which capture the “distribution and possession of culturally valued forms of knowledge which can be strategically used” (Archer et al., 2015, p930). The subcomponent considers both the knowledge that science qualifications are valuable as well as the sources of this knowledge who Adamuti-Trache & Andres (2008), quoted by Archer and colleagues, consider to be “key in the transmissions of cultural capital from parents to their children” (p1576). The ASPIRES2 project has noted the inequitable distribution of such knowledge and support in the UK, with less than a third of one sample of secondary school students reporting a positive experience with careers advice, validating the inclusion of this subcomponent within a model of science inequity (Archer et al., 2020).

This theoretical justification also applies to the relevance of careers knowledge to engineering: both science and engineering possess educational pathways and qualifications that would be advantageous to understand. However, as with other elements of the science capital model, it is unclear whether the subcomponent as framed by Archer and colleagues also equally captures engineering. Pathways for science and engineering are largely distinct, with a greater range of available pathways for engineering than science (T-levels, in addition to existing A-levels, Intermediate/Advanced/Higher Technical Apprenticeships, Degrees and Degree Apprenticeships). Whilst some overlap exists, such as the requirement of physics qualifications to enter some engineering pathways, overall, the two subjects might be seen as dissimilar in terms of pathways of entry. That engineering can be seen as more vocational than science is also a concern given previous identification that vocational progression knowledge within the UK is poor, in addition to the already poor level of career knowledge more generally (Hutchinson & Bentley, 2011; Walport, 2010).

The distinctiveness of knowledge for science and engineering in the UK is clear in recent literature, with those from more privileged backgrounds significantly more likely (64%) to know the steps to become an engineer compared to those from less privileged backgrounds (50%) whilst no significant differences were found between these groups for knowledge of how to become a scientist or healthcare worker (EngineeringUK, 2020a). This not only demonstrates that science and engineering differ in relation to symbolic knowledge, but also that this knowledge for engineering is less equitably distributed than science.

This distinctiveness is also demonstrated in how young people in the UK view science and engineering qualifications. One longitudinal study of secondary school students in the UK identified that science qualifications are seen as more likely (72.0%) to lead to a good job than engineering (48.5%) or Design Technology (41.2%) qualifications. This study also identified that changes to this form of 'symbolic knowledge' also differed with science increasing over two years (+5.3%) whereas engineering did not (-0.3%). These young people could be seen to have acquired institutional capital for science, but not engineering, demonstrating that changes to one do not necessarily affect the other and so delineating the two as separate (Hutchinson & Bentley, 2011). This distinctiveness is not navigated by the 'symbolic knowledge' subcomponent of science capital, questioning its relevance to engineering.

The ability of the 'symbolic knowledge' subcomponent to apply to engineering can be further questioned by analysing the role of teachers and parents which Archer et al. position as influential within this subcomponent. One study identified that UK STEM teachers and parents have less confidence giving careers advice for engineering (parents: 32%, teachers: 45%) than for science (parents: 36%, teachers: 58%) (EngineeringUK, 2019). These findings align with a lack of confidence amongst teachers with engineering more generally (Watermeyer et al., 2016). The low levels of confidence for engineering careers advice are salient given the importance of these relationships as outlined by Archer et al. and the dependency of young people on these sources, with 61% of one sample reporting they would approach a parent and 56% a teacher for such insight (EngineeringUK, 2020).

These findings indicate that the 'symbolic knowledge' subcomponent cannot effectively consider both science and engineering with a single measure as distinctions exist between these subjects. This questions the ability of the subcomponent to accurately reflect engineering – an assumption that it does so would overestimate the degree of capital a young person is judged to possesses for engineering.

Talking to Others About Science

The first of the two social capital subcomponents within Archer et al.'s science capital model is 'talking to others about science' defined as ascertaining "the frequency and number of people whom students talk about science in their daily lives" (Archer et al., 2015, p931). This considers how parents, teachers, family members, friends, extended family and scientists interact with an individual given previous recognition that social interactions with science support children in learning environments (Lyons, 2006). This subcomponent relates to the Bourdieuian concept of social capital, which Bourdieu defines as “the sum of the actual or potential resources that are linked to the possession of a durable network of more or less institutionalised relationships of mutual acquaintance and recognition—in other words, to membership in a group” (Bourdieu, 1986, p248). This subcomponent is therefore attempting to discern the degree to which social relationships support the development of and access to science capital.

This is validated by the work of Lyons (2006) and others who find that communication between individuals can benefit the development of science capital. Jackson et al. (2019) note that talking about science can support greater science career interest for some groups (though not all), highlighting both the value of this subcomponent but also the complexity of its effect in only influencing some and not others. The complexity of impact produced through talking to others about interests is noted elsewhere, with Pasupathi and Rich (2005) identifying that the attentiveness of the social audience will feed back and influence the interest of the speaker towards the topic of conversation: a speaker who encounters a bored audience will feel less interested in the topic they spoke about following the interaction. The content of social interactions can also determine the impact of its effect on individuals with Haden (2010) identifying that elaborative social interactions involving open-ended questioning produce richer learning outcomes for science and Crowley et al. (2001) noting that parental social interactions with children in science learning contexts can shape the engagement of children with learning. It is also noted that some social interactions can damage science aspirations, with Neblett and Cortina (2006) acknowledging that social influences are not always wholly positive in their impact.

The ‘talking to others about science’ subcomponent does not take into consideration many of these nuances, with little recognition of the potential for differential impact on different groups, the importance of the recipient attentiveness, and no examination of conversation content beyond the label of ‘science’. Whilst the subcomponent does explore frequency of communication, which is acknowledged as an important characteristic (Hare & Davies, 1994), the framing of this subcomponent might be seen as simplistic and presumptive that talking about science will lead to advantageous outcomes as a form of capital, which is not guaranteed as social *interaction* is not the same as social *support* (Rook, 1984). Whilst a simplistic measurement may have been inevitable due to the scale of data collection necessary to empirically access seven subcomponents, this does have important implications for how the subcomponent might apply to engineering, as this would require further steps of abstraction to presume a relevance.

Learning is widely acknowledged as a social process with social interactions noted to impact engineering learning and later recall (Benjamin et al., 2010). However, little research has explored this topic within engineering learning or the impact of science talk on engineering outcomes. Given the complexity identified in relation to talking to others and science aspirations it is perhaps unwise to assume a simplistic relationship between science talk and engineering. The lack of analysis of conversational content in Archer et al.'s 'talking to others about science' subcomponent means that there is no guarantee that the conversations measured by this subcomponent contain any engineering content (or, in fact, science content). The social partners considered in this subcomponent (teachers, parents, fellow pupils) are noted to possess a lesser level of knowledge or confidence with engineering as a topic compared to science (EngineeringUK, 2018; EngineeringUK, 2019). Whilst 'talking with scientists' is measured within the empirical measurement of this subcomponent 'talking with engineers' is not. As a result, social interactions for science and engineering should not be expected to be the same within the UK context amongst those considered by the 'talking to others about science' subcomponent.

Overall, the influence of social interactions for science must be recognised as a complex phenomenon but a valid one for consideration of science inequity. For engineering, there is limited evidence that science talk directly influences engineering and a synthesis of wider literature would suggest that talking to others about science and engineering in the UK is likely different. The structure of Archer et al.'s 'talking with others about science' subcomponent is simplistic and likely cannot access engineering as well as it does science. Further research is needed to establish the relevance of talking to others about engineering on engineering inequity.

Knowing Someone Who Works in a Science Job

The second of Archer et al.'s social capital subcomponents is 'knowing someone who works in a science job'. This subcomponent is supported by research that shows that children aged 10-14 with close family members employed in science-related jobs are more likely to aspire to science careers themselves (Archer et al., 2012) and research showing that motivation and encouragement from key adults is an important predictor of later educational choices (Mutjaba & Reiss, 2014). The advantageous capitals within this subcomponent are not specified, but the rationale for its inclusion is that these relationships can provide potential benefit through the mechanics of Bourdieuian social capital. This lack of specificity is unhelpful given the recognition that familial support is complex and not simplistic or linear in all cases (Archer et al., 2012). However, whilst not Bourdieuian in scope, the rich research literature on the influence of social relationships as role models supports the validity of socialised learning and its impact on aspiration (for example, Cheryan et al., 2011).

Having acknowledged the relevance of this subcomponent, despite its lack of specificity, we can next consider the degree to which knowing a science-employed individual might apply to engineering aspirations. Science and engineering careers often differ with distinct pathways, qualifications, accreditations, titles and working contexts. Knowing a science-employed individual cannot be seen to be the same as knowing an engineering-employed individual, so the direct relevance of this subcomponent to engineering aspiration is unlikely to be the same as its relevance to science. This would be confirmed by intergenerational career choice literature which explores the impact of parental occupation on later career of their child. This influence is relevant in the UK where a son is, generally, estimated to be 72% more likely to work in an occupation if their father is currently employed in that role (Bello & Morchio, 2022). This intergenerational influence is distinctly different for scientists and engineers, with 8.6% of engineers in one sample stating that they had an engineer for a parent compared to only 2.2% of scientists having a scientist parent (Laurison & Friedman, 2016). These findings highlight that in the UK context engineering and science are impacted differently by the same parental occupation influence, with engineering much more impacted by parental occupation than science.

The science capital subcomponent of ‘knowing someone who works in a science related job’ then can be seen as inadequate to examine engineering aspirations given that the influence of having an engineer parent is seemingly much greater than the impact of a scientist parent. Within one UK sample, engineering was found to have the second highest rate of intergenerational career choice, with only medical professionals having a higher rate of parents and child holding the same career role (Laurison & Friedman, 2016). These findings highlight that intergenerational influence of parental occupation – something that is very relevant within the Bourdieuian perspective – is distinct for engineering and science. This questions whether assessing science-employed social contacts such as in the science capital model can fairly represent the benefit of knowing an engineering-employed contact given that seemingly these two fields are uniquely influenced by such social capital.

Archer et al.’s framing of the ‘knowing a scientist’ subcomponent gives little recognition to the potential negative impact of knowing a scientist on science participation (thereby demonstrating a disadvantage not an advantage, and therefore not being considered a form of capital). Previous research has established that if children perceive their parental occupation as unpalatable the resulting effect of this occupation influence is more negative (Neblett & Cortina, 2006). This demonstrates that knowing a scientist is not an inherently positive influence and would further question the applicability of science capital to engineering given that feelings towards engineering are more negative than those for science generally in the UK (Moote et al., 2020). Differences between science and engineering would also affect the impact of maternal occupation, noted as a particularly impactful influence, due to the very low rates of female engineers (and therefore engineer mothers) in the UK (Korupp et al., 2002; Sikora & Pokropek, 2012). This further outlines the difference in how science and engineering social contacts may impact on young people and thus limiting the relevance of 'knowing someone who works in a science job' to the engineering domain.

Consumption of Science Media

Archer et al.'s model of science capital also contains subcomponents relating to behaviours and practices around science. The inclusion of these subcomponents is rooted in Bourdieu's view of arts-based cultural capital where the consumption and cultural practices of art were considered in relation to group distinctions. Archer and colleagues have replicated this approach to consider the cultural practices of science that may provide forms of capital to support science aspiration amongst some groups but not others. Given the lesser role of engineering within the UK education system, such behaviours and practices that do not relate to formal schooling may carry particular relevance to engineering inequity. The first of these behaviours and practices subcomponents is 'consumption of science media' defined by Archer et al. (2015) as capturing "the extent to which respondents consume science through various forms of media" (p930). This includes the consumption of television, books, magazines, and online sources. Given that media also exists for engineering it is reasonable to consider how well this subcomponent may relate to engineering.

Archer et al.'s theoretical positioning of media consumption as relevant to science inequity within a Bourdieuian framework is validated with research highlighting that media consumption can lead to greater cultural capital such as scientific literacy (in the form of scientific knowledge and understanding of science processes) and greater social capital (in the form of more home interactions for science) (Kelly et al., 2016; Penuel et al., 2010). The operationalisation of this subcomponent by Archer and colleagues is also valid, with measurement of frequency of media consumption and digital forms of media engagement included within this subcomponent strengthening its approach (Bohnert et al., 2021; Linebarger et al., 2009; Su et al., 2015). The inclusion of the 'consumption of science media' subcomponent can be seen as a valuable addition for understanding science inequity.

However, we must question the degree to which this subcomponent is inclusive of engineering. Archer et al.’s positioning of the 'science media consumption’ subcomponent positions media consumption as beneficial, in line with the Bourdieuian view of capital as an advantageous resource. However, media consumption research recognises the complexity of consuming media and the potential for disadvantageous outcomes. One investigation found that whilst some media content led to social, prosocial, cognitive and emotional development, other content led to greater aggression and lesser social and prosocial behaviour (Veraksa et al., 2021). This potential for disadvantageous outcomes is not considered in Archer et al.’s subcomponent (or many other framings of media consumption (see Byrne et al., 2021)) questioning its ecological validity. This also carries implications for the degree to which engineering is represented within this subcomponent, as these findings suggest a complexity to the influence of media consumption that would question a presumption that science media must also carry an advantageous influence on engineering.

As with other science capital subcomponents, and in line with the Bourdieuian perspective, it is important to consider the manner in which social relationships influence the development of different capitals for science. One study of the effect of science media consumption on the knowledge of science and inquisitive learning styles found little direct benefit on young children but did establish positive impacts on the parents who could then support their children in science (Bonus, 2021). This positive impact of media consumption on parents has been established elsewhere (Tabullo & Gago-Galvagno, 2021) and suggests that the benefits of media consumption for science may be mediated through social relationships, in particular those of the home environment (Watts & Bonus, 2021). The importance of social environment on the effect of media consumption is further validated by research that shows that whilst science media can build a greater interest in science (Levine et al., 2021), the frequency of engagement of young people with science media is influenced by parental attitude towards science. It can therefore be seen that parents may act as not only co-learners but as gatekeepers for science media (Sheehan et al., 2018). This validates the consideration of this subcomponent within a Bourdieuian view of science aspiration given that the benefits of media consumption – its advantages/propensity as capital – can be seen as mediated through the primary habitus/home environment of the young person.

The importance and influence of parents and teachers on the effect of media consumption would suggest that Archer et al.’s science media consumption subcomponent cannot apply to engineering in the same way it does to science. Parents, teachers and fellow students, who likely play such mediating roles in media consumption, are noted to carry different levels of knowledge, confidence, and attitudes towards science and engineering (EngineeringUK, 2018; EngineeringUK, 2019). These distinctions would suggest a differing level of impact on media consumption for science and engineering, highlighting the validity of considering engineering media in relation to engineering inequity but questioning the ability of the 'science media consumption' subcomponent to apply to engineering.

Participation in Out-Of-School Science Learning Contexts

The second behaviours and practices subcomponent included within the theoretical model of science capital is 'participation in out-of-school science learning contexts'. This is introduced as an attempt to understand participation with contexts in which capital for science might be acquired. This includes: "designed spaces (such as science museums, zoos/aquaria), community spaces (such as after-school science clubs), and everyday contexts (such as doing experiments/using science kits at home; fixing/building things at home; going on nature walks; programming computers" (Archer et al., 2015, p930). Such informal learning contexts and their educational benefits are well established in academic literature, though interchangeably referred to as 'self-directed learning' or 'life-long learning' (Johri et al., 2016). One estimate suggests that 85% of a student's time is spent outside of formal learning contexts, highlighting that 'out of school learning' can account for a large amount of lived experience (Gerber et al., 2001).

The recognition that these learning contexts are inequitably participated with validates the inclusion of this subcomponent within the science capital model. Out-of-school science learning contexts have been found to be more frequently participated in by white and middle-class groups or groups from particular geographic regions in the UK (Dawson, 2012; Department of Culture Media and Sport, 2011; Falk et al., 2015). Science learning contexts are recognised as imparting a complex benefit to participants including support for science aspirations of young learners (Archer et al., 2022; Callanan et al., 2011; Dou et al., 2019). Godec et al. (2022) establish that participation in informal science education is not necessarily governed by the interests of the child, but seemingly moderated by parental gatekeepers as with other subcomponents of the science capital model. Whilst acknowledging that the impact of out-of-school learning contexts on science participation is not a simple dynamic, these studies do highlight the relevance and value of considering out-of-school learning contexts within the science capital model of science inequity.

Research has also identified that out-of-school and in-school learning experiences are related, with Shaby and Vedder-Weiss (2020) identifying that the interactivity, positioning and role adoption of individuals will be the same in each context – a ‘non-science’ person in one setting will likely be a ‘non-science’ person in another. This might question the need to consider both in-school and out-of-school learning contexts within the science capital model, however, further research has shown that communication differs in these contexts. Parents with greater formal education communicate more scientifically than less educated parents within science museum settings, but they display few differences in home environments. Both science museums and home environments might be considered ‘out-of-school learning contexts’ demonstrating that under an equity lens these contexts display a complexity that necessitates a rich examination of differing out-of-school contexts. This supports the approach of theorisation and operationalisation of the subcomponent by Archer and colleagues.

Out-of-school learning contexts are notably important for engineering in the UK context considering that engineering features infrequently within the UK education systems, suggesting that learning experiences for engineering are disproportionately dependent on informal learning compared to science. Whilst less studied than science learning contexts, past literature has identified that engineering out-of-school learning contexts can lead to the development of capital such as mathematics learning, field experience and the development of team working skills (Denson et al., 2015). The impacts of out-of-school learning context for engineering, as with science, are noted to differ between groups with some contexts impacting men more than women whilst others impact both groups (Godwin et al., 2016). This highlights that the subcomponent is a valid one for a model of engineering inequity.

However, it is unclear to what degree out-of-school learning contexts for science are representative of those for engineering. Given the identification that parents play a mediating or gatekeeping role in out-of-school context participation and that parents are known to carry lesser knowledge and confidence with engineering than science; it might be expected that the impact of out-of-school contexts for science and engineering are not the same. It might also be questioned to what degree an out-of-school learning context for science may or may not include engineering, questioning its relevance to engineering inequity. Whilst out-of-school learning contexts are clearly important for engineering it is unclear whether the science capital model effectively captures these as well for engineering as it does for science, with no explicit examination of engineering out-of-school experiences. As a result, further examination is required.

Conclusions

This chapter has theoretically explored the relationship between the science capital model and engineering to determine the scope of this model and its potential application as a tool to address engineering inequity. By adopting a critical position that considers the distinctiveness of engineering and science, the science capital model was found to poorly represent engineering. Whilst an innovative and practically valuable model for science inequity, the relevance of science capital to engineering is theoretically poor with wider literature suggesting that the constituent subcomponents of science capital cannot apply to engineering in the same way as they apply to science.

For some subcomponents, such as scientific literacy, scientific-related dispositions/preferences, and symbolic knowledge of the transferability of science in the labour market a vital element of the subcomponent (habits of mind, particular attitudes, and educational pathways respectively) differs for science and engineering questioning the ability of this model to account for both subjects. This demonstrates that science and engineering differ for all three of the cultural capital subcomponents in this capital model. For other subcomponents, such as talking to others about science or consumption of science media, limitations of the theoretical and empirical framings of these subcomponents within the model make it difficult to understand the scope of effect and way these subcomponents relate to engineering but further theoretical insights suggest that these subcomponents would differ for science and engineering.

However, the theoretical critique outlined in this thesis does acknowledge that the capital perspective is valid for the engineering domain. Many of the science capital subcomponents are also acknowledged as potentially relevant for engineering if approached in an engineering-specific way. As a result, this analysis has supported the use of the Bourdieuian capital perspective to better comprehend and address the engineering inequities in the UK.

It must also be acknowledged that the science capital model is not only a theoretical perspective but also an empirical structure rooted in real world contexts of inequity. Whilst the analysis of this chapter has shown a misalignment between the theoretical model of science capital and engineering it is possible that this distinction is less impactful in the complex context of real-world application. Functionally, science capital may serve as an adequately successful tool for use in this thesis even if the model performs better for science than engineering.

These two conclusions identify a need to empirically examine the relationship between science capital and engineering to more conclusively determine the validity of adopting science capital to understand the engineering domain. The identification in this chapter that many forms of capital within the science capital model might also be approached in an engineering-specific manner raises the possibility of instead adopting an alternative, engineering-focused model of capital. In coming chapters of this thesis such models of capital will be empirically investigated to identify the strongest tool with which to develop greater understanding of engineering inequity. If empirical measurements of science capital are found to strongly align with engineering inequities the science capital model will be adopted. If an engineering-specific capital lens is found to outperform science capital then a novel model will instead be developed and applied to accomplish the objective of this thesis and develop a greater understanding of engineering inequities in the UK.

CHAPTER THREE: METHODOLOGY

Introduction

In previous chapters engineering inequities were identified as deeply entrenched within the United Kingdom, with longstanding issues of access, participation, success and representation within its engineering domain. It was reasoned that engineering inequities have persisted in the UK, in part, due to factors such as a dated cultural concept of engineering that has not evolved alongside engineering practices, a lack of engineering within the UK national curricula, and a shallow body of research examining the perpetuation of engineering inequities. It was argued that current understanding of engineering inequities possessed limited depth and practical value. The objective of the thesis thereby became to develop a greater understanding of engineering inequities within the UK context. A popular and influential model of science inequity, science capital, was considered for adoption to accomplish this objective. However, a theoretical examination of this model questioned the degree to which it might apply to the engineering domain necessitating further empirical study. In this Methodology chapter the investigation of this thesis is outlined to accomplish the objective of developing greater understanding of engineering inequities. First, a conceptual framework will be defined to position the understanding of engineering, inequity and the adopted Bourdieuian capital lens. Next, the research philosophy, design, sample and materials will be outlined. Finally, the research procedure and methodological limitations will be explored.

Conceptual Framework

The development of a conceptual framework within a body of research offers the opportunity to identify key concepts that are central to its objectives (Leshem & Trafford, 2007). Punch (2000) refers to the framing of these concepts as the 'what' and 'how' questions of research that support clarity and purpose. Within this thesis three key aspects are considered in relation to its objective of building greater understanding of engineering inequities in the UK.

Defining Engineering in the UK Context

The definition of engineering adopted in this thesis is critical in framing the subject matter and context of its enquiry. As noted in Chapter One, it is possible to define engineering in many ways. One widely accessible, socially constructed definition of engineering as 'making and fixing' is acknowledged based on the common public understanding of this domain (Institution of Mechanical Engineers, 2016; Institution of Mechanical Engineers, 2017; Marshall et al., 2007). However, this definition notably lacks a conceptual depth which limits its practical value within research. An alternative approach to defining engineering can draw upon the views of experts to highlight the importance of design, key engineering processes, engineering ways of thinking and acting (Dym et al., 2005; Haik, 2015; Huffman et al., 2018; Lucas et al., 2014; Pleasants & Olson, 2018; Winarno et al., 2020). This approach to defining the engineering domain offers greater nuance but is only drawn from an informed minority limiting the practical accessibility of its resulting definition. Adopting this definition within research would be an exclusionary practice that may restrict the potential pool of participants that are capable of engaging with the research. A definition drawn only from expert conceptualisations of engineering may also carry institutional influence that entrenches a certain, status quo interpretation of the domain that is at odds with the objectives of this thesis in facilitating change to engineering inequities. A further, relational definition of engineering considers the dynamic between engineering and other STEM domains, particularly science, noting the potential contribution of science, technology, and mathematics to engineering practices. Whilst engineering may be conceived of as similar to these other STEM domains such judgements are positional and depend on the context from which these comparisons are made. The relationship between engineering and other STEM subjects is considered to be a ‘family resemblance’: sharing common traits but not dictating perfect replication.

A definition of engineering is adopted within this thesis through a synthesis of these perspectives. Engineering is defined as: a practice of creative problem solving, commonly understood as ‘making and fixing’ but that can be more deeply understood as activities involving established design processes with the objective of creating effective and efficient solutions to identified problems. Engineering professionals can be understood to embody characteristics of engineering and its practice, including: an ability to visualise, think critically and systematically in identifying and deconstructing problems and forming creative and innovative solutions. Engineering can be understood as sharing some characteristics with other domains such as science, technology and mathematics with the nature of engineering as a practice presenting the opportunity to integrate insights of science, use of tools and technology and mathematics within engineering experiences. However, engineering must also be understood as distinct from these domains and considered as a singular domain with its own relationship to the UK and its population.

This definition can be seen to carry significant implications for the design of this thesis research project. The adopted definition recognises the need to navigate complexity in how engineering is understood and defined, offering a simplistic framing of ‘making and fixing’ alongside more complex understandings drawn from expert sources. This definition will remain accessible to the conceptualisations of the public, which is vital given the inequities central to this research enquiry are rooted within the general public. As a result, this definition will offer greater utility in data collection contexts; the adoption of an expert-only definition would damage the capacity to recruit effectively from the general public or would limit the ability to integrate research data with the conceptual framework of this project. Given that the core problem addressed by this thesis is related to understanding of inequity the managing of such exclusionary research characteristics must be carefully navigated.

The conceptualisation of engineering adopted within this research also carries implications for the philosophy and scope of the project. The research philosophy stemming from the thesis objective and this conceptual framework must acknowledge that 'engineering' is not a singular, natural aspect of the world but a construct developed through social consensus thereby dictating a recognition of social constructionist thinking. This definition also recognises the influence of cultural context on understanding, and therefore conceptualisations, of engineering. Such a philosophical positioning introduces further necessary considerations such as the potential for differing social contexts to carry distinct engineering definitions. This dictates the need to focus this research enquiry within the UK context and control for extraneous conceptualisations of engineering within international sources. The need for a UK-specific conceptualisation of engineering is supported by evidence, introduced in Chapter One, that shows that professional standards for engineering differ between international contexts (Zarharim et al., 2010) and that national cultural narratives of engineering likely influence contemporary conceptualisations of the domain. This complicates the research methodology as very little literature examines engineering inequity and education with a UK-specific focus; a greater body of literature is available in contexts such as Australia or the United States of America. However, this approach is crucial in order to preserve that validity of the conceptualisation of engineering and its focus on understanding and intervention with UK engineering inequities.

The definition of engineering adopted within this research justifies a similarly sceptical perspective on the utility and relevance of insights from other STEM domains. Engineering is framed as sharing a complex relationship with STEM: knowledge and skills from other domains are acknowledged as important within engineering practice, but engineering can still be distinguished independently of these STEM domains. Vitally to the focus of this research project, inequities in engineering and science are distinct with inequities much stronger in the engineering domain. However, inequities within the science domain have arguably received more attention and focus in interventions, such as with the science capital model outlined in Chapter Two. As a result, a large body of literature on science inequity is available in the UK that may be drawn upon within this research. Whilst it is necessary to adopt these insights mindfully the definition of engineering adopted in this research and its complex relationship with science can justify the use of these insights if proved to be valid for the engineering domain.

Overall, this definition of engineering can be judged as justified within the context of this research project and its objective of building greater understanding of engineering inequities in the UK. The synthesis of perspectives adopted in its formation support the theoretical underpinning and inclusivity of this definition. Such a conceptualisation will be applicable to a wide assortment of individuals, is based on UK-focused literature, and clear in its scope in relation to domains and contexts.

Conceptualising Inequity in Engineering

The second key concept within this research project is ‘inequity’ and its fundamental presence within the engineering domain. Within this thesis engineering inequity is understood as entrenched patterns of access, participation, success and representation which favour some groups over others leading to varied relationships with the engineering domain. As introduced in Chapter One, gender, ethnic and social class inequities are well-established within the engineering domain, skewing to a dominant profile of white males from more privileged socioeconomic backgrounds (EngineeringUK, 2018; 2018a; 2018b). However, a focus on such group differences must be acknowledged as superficial: relating to easily recognised categories (e.g. white, or male, or middle class) but lacking a deeper understanding of the underlying social mechanics which form and perpetuate these inequities over time. Conceptualisations of inequity in terms of fixed or relatively fixed characteristics such as social class or ethnicity are also less helpful in the development of interventions. For example, the knowledge that ‘girls are underrepresented in engineering’ does not intrinsically offer guidance on intervention strategies – further investigation is first necessary to better understand this patterned inequity and its underlying characteristics before strategies to address this inequity can be established and tested. The monitoring of representation based on such groupings is useful as an indicator of progress to equity but offers limited diagnostic value to inform change. More recent conceptualisations of inequity recognise its complex and intersectional nature but little such study of engineering inequities is present within current UK-based literature. Engineering inequities are understood to be a social injustice which see some groups unfairly underrepresented within the engineering domain. Engineering inequities are also recognised as a threat to economic wellbeing, and limiting influence on national and global resilience to challenges that require engineering solutions such as climate change or global pandemics. Such inequities are framed as a challenge to be overcome:

the objective of this thesis lies in developing a greater understanding of these inequities to facilitate effective intervention.

The engineering domain carries ubiquitous inequities present throughout society. The UK engineering workforce is deeply inequitable: only 16.5% of those in engineering occupations are female, only 11.4% come from non-white ethnic groups and there is a documented skew towards greater representation by those with more privileged backgrounds (EngineeringUK, 2022). Participation with educational pathways are similarly inequitable: only 19% of first degree enrolees in 2019/20 were female, whilst in 2018/19 only 1% of apprenticeship enrolees identified as black, and only 2% as British Asian (Department for Education, 2019; HESA, 2022). Inequities are even noted in earliest opportunities for educational decision making: in 2022 only 30% of Design and Technology GCSE enrolees in England were girls (Education Datalab, 2022). The scale and omnipresence of engineering inequities in the UK context imply a systemic presence of inequity that is entrenched within the national culture. As introduced in Chapter One, the culturally-rooted nature of engineering inequities is consistent with the rich historic and contemporary context of engineering within the UK and the various conceptualisations of engineering present within society. This framing of inequity as rooted in culture and society informs the way inequities are approached within this research.

The ubiquity of engineering inequities poses both challenges and opportunities for the methodology of this research project. It would be possible to study engineering inequities in many different contexts, groups or manifestations such as inequities of access or inequities of success. However, the objective of this thesis is concerned with the development of practical understanding that may aid in overcoming entrenched inequities in the UK. As a result, it is necessary to approach engineering inequities within this thesis in a manner that is congruent with this objective. In this thesis engineering inequities are therefore adopted in a manner that is relevant to secondary-school aged learners who represent the future generation of UK engineers. A greater understanding of inequity amongst this group may inform early interventions to remedy unequal patterns of access, participation, success and representation within the engineering domain. Engineering inequities are thereby conceptualised in relation to future orientation towards engineering education or careers. This adoption is supported as valid by identification of engineering inequities amongst secondary school-aged learners and the importance of formative experiences for the shaping of identities (Archer et al., 2013; Hutchinson & Bentley, 2011). Where engineering inequities amongst adults may be examined in relation to current occupations or educational qualifications these metrics are not feasible for learners early in their journey through education. As a result, aspirations for engineering are considered as an age-appropriate concept of inequity. Such aspirations are well recognised as inequitable amongst secondary school-aged learners validating this conceptualisation (EngineeringUK, 2021; Hutchinson & Bentley, 2011). Aspirations for future engineering education or careers can therefore be adopted as a key form of engineering inequity that represents the alignment of a young learner to a future in the engineering domain.

Adopting a Bourdieuian Perspective

This thesis adopts the work of Pierre Bourdieu to explore the distinctions within social groups that underpin engineering inequities. Originally developed to understand the endurance and reproduction of social class groups, Bourdieu's framework developed over several decades as a method of conceptualising power dynamics and the social mechanisms that underpin societal structure. This large body of work offers the concepts of habitus, field and capital as interconnected thinking tools to explore the process of inequity in a manner that is sensitive to social and cultural context. These tools can facilitate a deeper understanding of the mechanics of inequity in line with the recognised need within this thesis to move beyond simplistic group descriptions of gender, ethnicity or social class in understanding engineering inequity.

Habitus represents one of the earliest concepts within Bourdieuian thinking (Maton, 2014). In early writing Bourdieu framed habitus as a set of dispositions: "[designating] a way of being, a habitual state (especially of the body) and, in particular, a predisposition, tendency, propensity or inclination" (Bourdieu, 1977). An individual's habitus is understood to develop as a result of socialisation during childhood; individuals internalise the characteristics of those around them leading to a likeness that propagates group characteristics and social identity which is then in turn mirrored by the next generation. The habitus "acts within [individuals] as the organizing principle of their actions" acting to shape physical tendencies (such as posture or accent) as well as psychological qualities such as perception, reasoning and interpretation, emotional expression, and habits of thinking and behaviour (Bourdieu, 1977; Maton, 2014; Wacquant, 2014). The concept of habitus has been adopted to examine many contexts including social class (Bourdieu, 1977), and later gender (McNay, 1999), race (Sallaz, 2010), education (James et al., 2015), agrarian lifestyles (Sutherland & Darnhofer, 2012), drug use (Parkin, 2016), and more. It is therefore reasonable to consider that habitus may provide insight into engineering inequities: this tool may offer a valuable perspective on the dispositions of groups that are, or are not, represented within the engineering domain and the cultural context in which these inequitable groups are entrenched and perpetuated over time. As an embodied and physical practice engineering is likely compatible with the thinking tool of habitus and its perspective on embodied social identity.

Bourdieu's notion of field relates to a social context in which an individual operates. This social arena "contains people who dominate and people who are dominated. Constant, permanent relationships of inequality operate inside this space, which at the same time becomes a space in which various actors struggle for the transformation or preservation of the field" (Bourdieu, 1996, p40). Power dynamics are understood to depend on the field context, necessitating a clear understanding of the social context in which analyses take place. This concept can enrich the understanding of engineering inequity within this thesis, taking into consideration the power dynamics and social landscape within engineering relevant contexts that may contribute to patterns of engineering inequity. The rich cultural context of engineering in the United Kingdom outlined in Chapter One demonstrates the complexity within this domain supporting the relevance of field. The field concept (like many other developed or utilised by Bourdieu) is a thinking tool. In this way a field context does not need to relate specifically to a physical space but can instead stress the need to acknowledge the specific 'rules' and 'powers' individuals may possess in varied settings. This is relevant to the contexts in which power dynamics play out to shape engineering inequities.

The concept of 'capital' is arguably the most popular of Bourdieu's conceptual tools. For Bourdieu, capital represented particular assets (which could also be referred to as resources) that are put to productive use to obtain an objective. Contrary to more traditional economic views of capital, Bourdieu saw these resources as not only financial but cultural or social in nature. These concepts were explored and refined over several decades to form the now popular concepts of cultural and social capital within the Bourdieuian framework (Bourdieu, 1984).

Cultural capitals were devised by Bourdieu as 'cultural goods' that are developed by an individual over time and might include tastes, knowledge, skills, credentials, or possessions. Cultural capital could be embodied (internalised within the self), objectified (owned as material property), or institutional (formally certified and recognised qualities, such as professional rank or qualifications). Bourdieu argued that these qualities become resources if they align with the dominant culture of a given context or 'field' (Bourdieu, 1986). For example, possessing refined table manners is a resource in the context of a dinner party but may not be as valuable in other contexts such as a football match or whilst commuting to work. For Bourdieu, cultural characteristics could be valuable, transferable for other resources, and advantageous to possess – the characteristics that determine the power of economic capital. Bourdieu reasoned that capitals do not inherently carry value, but that their value is decided by powerful gatekeepers in given contexts which results in the self-legitimisation of the characteristics of the powerful in a manner that perpetuates their influence and ensures a continuity of inequity.

The Bourdieuian framework also considers social capital: “the sum of the actual or potential resources that are linked to the possession of a durable network of more or less institutionalised relationships of mutual acquaintance and recognition—in other words, to membership in a group” (Bourdieu, 1986, p21). For Bourdieu, an individual’s social position or status determines the degree to which they can access resources that are available to them through their social network. As social position/status is determined by the possession of capital and the context of field, social capital is deeply connected to cultural capital. Knowing someone who has access to resources is not valuable to an individual if they do not possess the status to be recognised as deserving access. Social capital therefore offers an insight into the creation and maintenance of groups, particularly groups of power. The concept of the ‘old boys’ club’ represents a keen example of Bourdieuian social capital in action: the group maintains their membership through exclusively admitting those possessing particular resources, thereby increasing the resources available to the select group whilst individually benefitting from potential access to these scarce resources. In this way the concept of Bourdieuian social capital can help to understand the structure of social groups within society and the distribution of valued resources.

Cultural and social capital are deeply insightful concepts that can be brought to bear to better understand engineering inequities. Rather than considering inequity through a generalising lens of gender, ethnic, or social class identities it is instead possible to explore engineering inequities in relation to the possession of beneficial resources, or capital, that support individuals to enter and prosper within the engineering domain. Understanding who possesses capital for engineering may offer a valuable perspective on the mechanisms through which engineering inequities are perpetuated. Formative applications of the Bourdieuian perspective within classroom settings supports its validity for use with secondary school-aged learners. The Bourdieuian conceptual toolkit may thereby support the development of a richer understanding of engineering inequity and its perpetuation in entrenched patterns of access, participation, success and representation.

The Bourdieuian framework was principally developed to examine the context of social class reproduction: the intergenerational perpetuation of stable social class characteristics and position. This would suggest a relatively pessimistic interpretation of inequity that is inconsistent with the objective of this thesis in supporting intervention to challenge engineering inequities. This criticism of determinism is softened, however, with the acknowledgement of what Bourdieu and Passeron framed as ‘explicit pedagogy': the capacity to overcome one's dispositions and the subconscious influence of habitus through conscious intervention (Bourdieu & Passeron, 1977; Yang, 2014). This 'soft determinism' is arguably very consistent with the positions of this thesis that frame engineering inequity as deeply entrenched but capable of being intervened with, supporting the adoption of the Bourdieuian lens. Bourdieuian theory may also be criticised as dependent on 'deficit thinking': positioning that inequities occur due to a deficit of capital amongst some groups. Deficit models are criticised as overly simplistic and unfair in positioning blame on individual or group failings rather than contextual or systemic factors (Smit, 2012). Whilst Bourdieu proposes a deficit mechanism of capital – with those possessing lesser capital less capable of putting their resources to beneficial productive use – this perspective also acknowledges that the value of capital is arbitrarily determined by the self-perpetuation of the powerful as opposed to a consequence of individual failing. As a result, Bourdieu's perspective may be understood as avoiding a major issue of deficit thinking that would limit its utility in contemporary contexts.

A further, more valid, criticism questions the enduring relevance of the Bourdieuian framework given its theoretical foundations relate to now dated conceptualisations of society and its power dynamics (Prieur & Savage, 2013; Sullivan, 2001). These criticisms note that Bourdieu's positioning of 'high arts' as the legitimate culture of the powerful is questionably relevant to modern society and aligns with wider reflections on the duality of science and arts in modern contexts (Snow, 2012). This criticism is supported by a growing body of literature that finds little empirical value in Bourdieu's traditionally framed concepts (Stopforth & Gayle, 2022). However, it is possible to recognise this criticism - and others outlined earlier - and still adopt the Bourdieuian perspective in a 'relative' rather than 'absolute' manner (Prieur & Savage, 2013). Such a position was adopted by Archer et al. (2015) with the recognition of 'science capital', noted in Chapter Two, as a more relevant 'legitimate' form of capital for contemporary times. This position is consistent with that of Savage et al. (2005) who note that contemporary adoption of capital offers a robust and useful approach to understanding the impact of accumulated resource and its transferability to access other resource. Bennett et al. (2009) similarly find an enduring value to the Bourdieuian framework, if approached in a more contemporary fashion.

This thesis will adopt such a 'pragmatic' or 'practical' interpretation of the Bourdieuian framework. Noting the value of Bourdieu's perspective, engineering inequities will be examined in relation to capital and habitus in the wider UK field. This domain-specific adoption will not subscribe to all sociological or philosophical implications of this significant, and at times dated, body of literature. However, as a set of thinking tools the Bourdieuian lens may still offer a nuanced perspective on how engineering inequities continue to perpetuate within the UK – similar to the insights developed by Archer et al. (2015) in their science capital domain-specific application of Bourdieuian thinking.

Methodology

Research Philosophy

This thesis adopts a pragmatic research philosophy to develop understanding of engineering inequities in the UK. A pragmatic research philosophy rejects strict interpretations of research philosophy (such as positivism or interpretivism) and instead recognises that research questions will at times demand a synthesis of strategies and perspectives to most effectively form insight and solutions (Morgan, 2014). In this way, pragmatic research is utilitarian or may be framed as 'common sense'. This approach fits the solution-oriented focus of this thesis and its recognised issue of poor understanding of engineering inequities. A pragmatic approach is certainly valid for the context in which this thesis takes place with the Covid-19 pandemic applying a myriad of challenges which conflict with traditional approaches of doing research and demand novel solutions.

Pragmatic research also does not accept overly abstract or overly fixed ideas and similarly rejects the interpretation that only one 'true' reality exists. 'Truth' is recognised as changeable in response to time and views knowledge as a construct produced through experiences in the real world. This is compatible with the Bourdieuian conceptual framework adopted within this thesis and the definition of engineering, developed in Chapter One, which acknowledges the varied conceptualisations of the domain active within the UK context. Pragmatic approaches are noted to facilitate a synthesis of positions and perspectives which will be necessary in the development of understanding of engineering inequity (Morgan, 2014). Little past research has explored this topic in a sophisticated manner in the UK, and Bourdieuian capital is acknowledged as a deeply cross-cutting lens that recognises many differing factors. The pragmatic approach – less bound to the tribes of either positivism or interpretivism – is therefore more compatible with the necessary approach to most effectively form a greater understanding of engineering inequity within the adopted conceptual framework.

Research Aim and Questions

The aim of this thesis, as outlined in Chapter One, is to develop a greater understanding of engineering inequities in the United Kingdom in a manner that can inform impactful interventions and support young learners to become engineers. To accomplish this the thesis is structured around two main lines of enquiry. The first explores whether the science capital model, as a widely acknowledged model of science inequity, also applies to the engineering domain. This is examined theoretically and empirically in Chapters Two and Four. The second line of enquiry considers whether it is possible to draw on a domain-specific application of Bourdieuian capital to develop an engineering-specific model of capital that will fulfil the aim of this project and increase understanding and intervention of engineering inequities in the United Kingdom. This is examined in Chapters Five to Eight. Specific hypotheses are included in empirical research chapters throughout the thesis.

Research Design

The adoption of a pragmatic research philosophy or the Bourdieuian capital framework do not dictate a particular methodological design as both quantitative and qualitative methods are relevant to pragmatic methods or the exploration of capital (Mobley et al., 2013; Tzanakis, 2011). This is consistent with the recognised objective of developing greater understanding of engineering inequity, which might be undertaken in many differing ways. However, past science capital literature largely draws upon quantitative methods (DeWitt et al., 2016; Moote et al., 2021). This is particularly the case within the initial development of the science capital model and instrument (Archer et al., 2015). To this end a quantitative-dominant questionnaire-based research design was adopted within this thesis.

A questionnaire-based research design was justified for a number of reasons. One of the most important justifications for the adoption of a questionnaire-based research design was the feasibility of this research method during the Covid-19 pandemic. Limitations on social contact limited the degree to which individuals could meet or interact which dramatically affected the range of research methods available for adoption. Case studies, interviews, focus groups or other qualitative methods were less feasible in this climate. Whilst adaptions could have been adopted to facilitate these methods, such as the use of online video messaging to conduct interviews, these efforts were judged to be too labour and time intensive and incompatible with the demands on the education sector. However, a questionnaire-based data collection could be introduced remotely with relative ease and collected through a single time-point minimising the pressures of participation for both researcher and participants.

The use of this approach allowed existing resources to be drawn upon and integrated into the investigation of engineering inequity. The science capital instrument developed by Archer et al. (2015) is a key example of this, providing a valid and reliable instrument of capital within the STEM domain. Whilst the conceptual framework of this thesis questions the utility of using science resources in an engineering domain the use of a questionnaire design allowed this uncertainty to be tested using existing tools including the science capital instrument. A questionnaire-based project was also justified as consistent with the science capital development process used by Archer et al. (2015) to form their model supporting the potential development of an engineering-specific model through this research methodology. For these reasons a questionnaire-based design was compatible with the objectives of this thesis in developing knowledge, providing a means to draw on existing literature and support the validity of the advancement of understanding aimed for within this work.

A questionnaire-based quantitative design was determined to facilitate the largest scale data collection in the time available for this PhD research project. As the topic of this thesis concerns entrenched national patterns of inequity within engineering it was necessary to collect a large dataset to represent the sampled population as reliably as possible. A quantitative approach utilising a questionnaire design was justified as offering data collection opportunities from a greater geographic range and from a larger number of participants compared to more time-intensive qualitative approaches (Fraenkel et al., 2012). The offering of digital or physical versions of this questionnaire also contributed to a wider and more affordable research project.

Quantitative data collected through a questionnaire design also offered needed opportunities to confirm the validity and reliability of collected data – an important aspect of the objective of this thesis in advancing understanding. The ability to statistically test the reliability of collected data and examine the dimensionality of presumed underlying relationships can support the confidence of conclusions drawn in the development of knowledge. The lesser role of subjectivity within quantitative data analysis similarly justifies the adoption of a questionnaire design. Given the limited understanding of engineering inequities within the UK subjective conclusions drawn through qualitative methods could not be tested in a sufficiently rich manner against current knowledge. This issue is lessened for quantitative analyses which are validated by objective statistics as opposed to subjective interpretation (Arghode, 2012).

For these reasons, a quantitative questionnaire-based approach was deemed the most reasonable and pragmatic given the context in which this thesis took place.

Participants

Secondary school-aged young people (aged 11-16) were chosen as the target population of this research enquiry. As noted in the conceptual framework, engineering inequities are observable throughout UK society with many inequitable patterns of access, participation, success and representation amongst many groups. Many populations could therefore potentially have been drawn on to support this research. However, it was judged that secondary school-aged young people were the most effective and relevant population to consider in relation to the objective of this thesis to develop greater understanding of engineering inequities in a manner that might address entrenched issues within the engineering domain. Secondary school-aged learners will not yet have begun their journey towards (or away from) engineering education or careers. Individuals in this group will either be about to, or have just, made the first decisions to shape their educational trajectory. The popular 'pipeline theory' envisions the journey into domains as a 'leaky pipeline' with losses at key transmission points which represent individuals abandoning their trajectory into the domain (Department for Business Innovation and Skills, 2013). Secondary school-aged learners will be very early in their potential journeys towards engineering and therefore represent a group that is not institutionally partitioned – or 'lost from the pipeline' – for engineering based on previous decisions. The same could be said for primary school-aged learners, however it is expected that secondary school-aged learners will possess a more sophisticated understanding of engineering than younger age groups which facilitates their inclusion in this research process. Given the early indications of engineering inequity noted for secondary school-aged learners this group were justified as a valid sample to explore the early shaping influences that affect engineering trajectory (Archer et al., 2013; Hutchinson & Bentley, 2011). As the group positioned closest to the point in which decision making for engineering will take place, secondary school-aged learners represent a key target group to examine in relation to engineering inequities. This includes both educational and career aspirational inequities which would be examined within this thesis.

A non-random, opportunity sampling technique was adopted within this thesis due to the pressures of the collecting data during the ongoing Covid-19 pandemic. Schools were identified through existing relationships to the researcher, through publicly available listings of schools and contact information or through third party organisations such as Primary Engineer, UniConnect regional teams, or Local Enterprise Partnerships. Identified schools were contacted and provided with a short summary of the research project, an offer to participate and full briefing document (see Appendix A). Interested schools were provided with a gatekeeper consent form for completion and then entered into the project. This opportunity, non-random sampling method is notably a weaker approach to data collection, which may introduce bias or a lack of representation. Care was taken when contacting schools to offer participation to learners from across the UK, in particular representing all areas of England, Wales, and Scotland (contact with Northern Irish schools was somewhat lacking due to time pressures). These efforts attempted to limit the impact of non-randomness within the sample but this in unavoidable without an extensive, time consuming process of randomisation. Such an undertaking may have been beyond the scope of this PhD project in normal times, with millions of learners in secondary education in the UK, however the pressures on schools during and following the Covid-19 pandemic added further difficulty to the development of a truly random sample. As a result, the thesis sample was justified within a pragmatic research methodology but must be considered as non-representatively recruited.

Data was collected from 921 secondary school-aged (11 to 16 years old) students from ten schools in England and Scotland. Eight schools were located in England and two in Scotland. Of the 921 participants, N=505 (54.8%) were female and N=388 (43.4%) were male whilst 28 (3%) gave no or a non-binary gender identification. Most participants came from English schools, N=832 (90.3%), with 89 (9.7%) studying at Scottish schools. Participants were recruited from all secondary school-age groups: ages 11-12 (N=152, 16.5%), 12-13 (M=282, 30.6%), 13-14 (N=167, 18.1%), 14-15 (N=274, 29.8%), and 15-16 (N=41, 4.5%). Overwhelmingly the sample reported a white ethnic background (N=856, 92.9%) with little representation by British Asian (N=1, 0.1%), black (N=5, 0.5%), Chinese or East Asian (N=4, 0.4%), Middle Eastern (N=3, 0.3%), or other/mixed (N=23, 2.5%) ethnic backgrounds, whilst a small number of participants did not provide their ethnic background (N=29, 3.1%). This is a challenge to the ability to examine inequities in the ethnicity of engineering however due to the opportunity sampling approach and impact of Covid-19 further sampling to remedy this was not possible.

Materials

Project Materials

Research materials were developed to support the recruitment of participants and data collection. Schools received a briefing sheet when contacted to participate with the project. If they wished to participate they received a gatekeeper consent form, copies of the questionnaire, and a support document for delivery of the questionnaire to pupils. Participating learners received a briefing sheet, consent form, and debrief document. These research materials are included in Appendix B.

Data Collection Questionnaire

A single data collection questionnaire was developed and adopted within this research project. A cross-sectional data collection strategy was utilised within this questionnaire to collect data only once per participant. A single point of collection was deemed least disruptive to schools given the legacy of disruption from the Covid-19 pandemic school closures. This single point of collection necessitated the collection of all research data at one time, leading to the development of a larger questionnaire containing several subcomponents. Data collected through this approach would then be used throughout the investigations of this thesis. The questionnaire was available as both a physical and digital resource to ease participation for schools.

The questionnaire contained 170 items examining many aspects relevant to the thesis enquiry. The complete questionnaire is available in Appendix C; scales are outlined in sections below and expanded upon in Appendix D.

Sample characteristics: Participants were asked a series of questions to characterise themselves which were drawn on to examine how representative the sample was in relation to the population and provide grouping characteristics that could later be examined within statistical data analyses.

Gender: Participants were asked to provide a gender identity to facilitate an examination of gender grouping given the recognised gender inequities within UK engineering ("Are you a girl or boy? Girl, Boy, Other Identity").

School name: Participants were asked to provide the name of their school to allow school-based comparisons and identify the geographic region represented within the sample ("What is the name of your school?").

Year group: Participants were asked to report their current year of schooling to determine their progression through the education system and age ("What year group are you in?").

Ethnic identity: Participants were asked to provide their ethnic identity to facilitate an examination of ethnicity given the recognised ethnic inequities within UK engineering ("Which of the following best describes your ethnic origin?").

School sets for science, mathematics and English: Given past literature had acknowledged that Bourdieuian capital differed between groups within school set structures it was necessary to examine the relationship between inequity and academic ability. It was not possible to examine the secondary school-aged participants in relation to academic ability for engineering as this is not a curricular subject for most learners in the UK. Instead, academic ability in the science, English and mathematics domains were examined through questioning which academic set the participant belonged to for classes in each domain ("Which of the following statement below is true for you now? I am in one of the top sets, middle sets, bottom sets, there are not sets in my school."). Set structure is likely a reasonable approach to assessing general academic ability, within an institutional definition of 'success', given the propensity of UK secondary schools who adopt an academic ability hierarchy within their set structures (Jerrim, 2019).

Social class: As past literature had identified that UK professional engineers skewed towards greater socioeconomic privilege it became necessary to consider the social class of participants (EngineeringUK, 2018; Friedman et al., 2015; Friedman & Laurison, 2020). This was measured in two ways, recognising that social class is not only an economic condition but a social condition entrenched within cultural identity (Savage, 2015). To examine this economically, the Income Deprivation Affecting Children Index (IDACI) sub-index of the Indices of Multiple Deprivation (IMD) measure was adopted. This measurement examines the proportion of all children aged 0 – 15 within a region who are in deprived families where deprivation is defined in relation to out-of-work parents or those in work but with low earnings (Ministry of Housing, Communities and Local Government, 2019). To utilise this measurement index participants were asked to provide the postcode of their home address for use in accessing the IDACI score for their home environment. This was only possible in England as the IMD relates only to English local wards. To also examine the cultural identity characteristics of social class, the general cultural capital measure, outlined later in this section, was used to determine the class of participants from a Bourdieuian perspective. Given that the Bourdieuian framework was initially developed to assess social class differences this tool represented a convenient way of also examining social class from a non-economic perspective. Past literature validated the adoption of this tool to understand social class identity (Lareau, 2011; Sullivan, 2001).

Conceptualisation of science and engineering: A number of items were included to assess how participants conceptualised the engineering and science domains. This included two multiple choice items ("When you hear the word 'science'/'engineering' what comes to mind?"). Two free response items also asked participants to name careers that they attributed to the science or engineering domains ("Can you think of any science/engineering jobs that a university degree could lead into?").

Educational experiences with science and engineering: A number of items were included to examine the science and engineering educational experiences of participants. Learning experiences are acknowledged as inequitably experienced in the UK validating this consideration within the investigation of engineering inequity (Dawson, 2012; Falk et al., 2015). One multiple choice item assessed the recognition of engineering within participant classroom experiences ("Have you come across engineering in your education so far, and if so where?"). Two items examined the experience of participants with extra-curricular learning experiences in science ("Have you participated in any science education programmes or competitions? E.g. CREST Award, Project Bloodhound, Science Fairs, Olympiads, or others?") and engineering ("Have you participated in any engineering education programmes or competitions? e.g. Secondary Engineer, Science Fairs, Ultimate STEM Challenge, or others?"). Follow up questions determined which programmes or competitions that had been experienced, or if no experience had been encountered whether the participant would wish to take part in the future.

General cultural capital: A six-item measure of general cultural capital was adopted from previous literature to facilitate a comparison between newer models of capital such as science capital and the traditional Bourdieuian conceptualisation of cultural capital. This cultural capital measure also served as a Bourdieuian classification of social class. Parental education level, access to reading materials and participation with beaux arts learning contexts were measured, in line with past measures of Bourdieuian cultural capital (De Graff et al., 2000; Stopforth & Gayle, 2022). The inclusion of this instrument not only facilitated a direct comparison of findings with the conceptual framework of Bourdieuian capital but offered a further method of conceptualising social class. See Chapter Four for more information on this instrument.

Science capital: The 14-item science capital instrument developed by Archer et al. (2015) was adopted to calculate science capital scores for participants. This instrument was adopted to facilitate a direct comparative measurement against previous findings in the science capital literature. Past literature has drawn on this instrument to examine STEM inequity (Archer et al., 2015; DeWitt et al., 2016; Moote et al., 2020; Moote et al., 2021). See Chapter Four for more information on this instrument.

Engineering capital: Items were adopted to examine forms of engineering capital, informed by the work of Archer et al. (2015) and others. This included measurement scales for: engineering literacy, dispositions, knowledge of pathways, social connections to engineers, engineering learning experiences and media consumption, linguistic and familial resources for engineering, and more. See Chapters Five, Six and Eight for more information on these instruments.

Engineering aspirations: Given the focus of this thesis on developing understanding of engineering inequity it was necessary to effectively measure these inequities amongst secondary school-aged learners. Measuring access, participation, success and representation amongst this group introduces several challenges. First, engineering equity is more difficult to examine within a school-aged sample than, for example, science equity as engineering is not a curriculum subject. Participants cannot be examined in relation to their past participation with engineering classes, or achievement in engineering assessments, or representation in elected study (beyond a GCSE for Design and Technology, which whilst valid is questionably aligned to engineering and engineering pathways as discussed in Chapter One). Second, the use of a secondary-school aged sample dictates that few opportunities will have yet presented themselves to participants to self-select engineering pathways resulting in little inequity in participation. Due to the compulsory nature of a nationally prescribed curriculum, participation with subjects is largely homogenous throughout secondary education in the UK. An examination of *present* indicators of trajectory for engineering would demonstrate little, necessitating the need to approach *future* trajectory inequities. To do this, participants were asked about their intention to study or work in the engineering domain in the future. The desire to study or work in engineering could be considered as a representation of alignment or trajectory to future engineering activity. Inequities in engineering education or careers are observed as soon as these pathways become available to young learners suggesting that inequities in alignment to these subjects are active before the opportunity of decision making. As a result, engineering inequities might be expected to already be present within a secondary school-aged sample despite the lack of opportunities to yet act on this in decision making. Secondary school-aged learners are a particularly valid population to consider in this manner given this period of education is where decision-making for educational trajectory is first offered to learners.

To empirically examine engineering educational and career aspiration, three items were included in the questionnaire. To assess engineering educational aspiration an item asked participants whether they wished to study engineering following their secondary education ("Although it is a long way off, which of the following describes your views: I would like to study engineering at university, at college/sixth form, after GCSE/National 5s but not A-Level/Highers, I do not want to study any engineering after GCSE/National 5s, None of the above or I don't know"). To assess engineering career aspiration participant interest in engineering careers was established with two items ("Do you think you might like to work in an engineering-related job in the future?" and "I want to become an engineer").

Engineering identity: A four item measure of engineering identity was also included as a further instrument to understand the relationship between the individual and the engineering domain. This instrument drew on Archer et al.'s (2015) approach to conceptualising identity. See Chapter Four for more information on this instrument.

Engineering engagement: A twelve-item instrument of engineering learner engagement was developed to examine the relationship between participants and alignment to learning in the engineering domain. This drew on engagement literature, in particular topics of affective and cognitive engagement (Eccles &

Wigfield, 2002; Fredricks et al., 2004). This instrument allowed deeper inequities in how participants viewed and experienced engineering to be examined. See Chapter Eight for more information on this instrument.

Procedure

This PhD project originated as a funded studentship from the University of Central Lancashire with the project topic developed in collaboration with the engineering educational organisation Primary Engineer in 2019. The topic of this research studentship was relatively open but generally concerned with engineering education in the UK context and the learning experiences of young people who encounter curricular-mapped engineering learning. The project began in October 2019.

The first two months of this project, October to December 2019, were spent developing the topic through examination of past and current literature on engineering education in the UK context. The topic of engineering inequity was identified as deeply significant to both the educational context of engineering but also the wider engineering domain. A lack of equity within the engineering domain was recognised as fundamentally impactful to the economic topic of skills supply and sociological topic of social justice and diversity. Inequities were identified as systemic to the engineering domain, manifesting in various forms throughout educational, professional and societal contexts. This period of literature study highlighted a lack of engineering-specific literature on education and equity within the UK context. Whilst represented within STEM-based perspectives little literature delineated the specific influence of engineering inequities within educational or career settings. Less literature still considered engineering inequity in a sophisticated manner. This period of critical literature synthesis led to the focusing of this thesis topic on the need to develop greater understanding of engineering inequities in the UK, particularly amongst young learners, in a fashion that might support more effective interventions to build greater engineering equity. The science capital model was identified at this time as a strong theoretical and empirical perspective on science inequity – however, it was unclear to what degree this body of work might apply to the engineering domain. What little literature had examined this directly was inconclusive or judged to be methodologically problematic. The potential adoption of this science capital model to accomplish greater understanding of engineering inequities was thereby also identified.

Following the identification of the thesis objective a methodology was designed to develop greater understanding of engineering inequities. This methodology would involve the empirical investigation of science capital to determine its relevance to the engineering domain. Should, as expected, this model be found to fit poorly with the engineering domain then a novel engineering-specific model would be developed. A quantitative research design was identified as most compatible with the empirical measurement of science capital supporting the use of a questionnaire design. Qualitative methods of focus groups and interviews with learners and teachers would also be adopted later in this thesis to triangulate deeper insights concerning engineering inequities. This proposal was submitted for Research Programme Approval in December 2019.

From January to March 2020 preparation for this investigation began including further reading and the development of research materials in preparation for a submission for ethical research approval. However, in March and April 2020 the impact and expected longevity of the Covid-19 pandemic demanded modification to the research plan. It became clear that whilst it may have been possible to conduct questionnaire data collection (albeit digitally) it would be impossible to take part in face-to-face data interviews or focus groups due to the implementation of social distancing guidance. The unprecedented nature of the pandemic impact introduced significant uncertainty as to the possibility of completing this project as designed. From March to June efforts were instead shifted to a theoretical investigation of engineering inequities. It was decided that empirical data collection would be attempted, but that the thesis may require a greater focus on theoretical examination if the current context made data collection impossible. An ethics review of the project was submitted and approved in October 2020 with the refined objective of completing remote questionnaire data collection within secondary schools. The thesis would continue to focus on the need to develop greater understanding of engineering inequity through the testing of science capital and development of a novel engineering-specific lens. However, in light of the pandemic restrictions, no in person data collection would take place.

From November 2020 to June 2021 secondary schools were recruited to participate with the research project. Schools were recruited through existing relationships with the researcher, collaboration with third party organisations such as Primary Engineer and cold-calling to schools utilising publicly available contact details. Ten schools were recruited during this time and participated through physical or digital versions of the developed questionnaire. Thesis writing continued during this period focusing on the theoretical aspects of the project.

From July 2021 to April 2022 the collected data was aggregated, processed and analysed using the SPSS statistics software to accomplish the objective of the thesis. First, the validity of the science capital perspective to the engineering domain was empirically examined. A science capital score was calculated for each participant and statistically examined to determine its relationship to engineering inequity (see the Chapter Research Methods section of Chapter Four for further details on this process). A similarly structured but simple measure of engineering-specific capital was also examined with analyses determining that an engineering-specific approach was a more insightful lens on engineering inequity. These findings supported the development of a more sophisticated engineering-specific model of capital to better understand inequities in trajectories for future engineering education or careers. Next, the development process used to form science capital was examined and adopted to create such a model of engineering capital. This four-stage process was undertaken to first theoretically and then empirically structure and validate a measure of engineering capital (see the Chapter Research Methods sections of Chapters Five, Six and Seven for further details on this process). This engineering capital model was found to be a valid and insightful lens on engineering inequities that both aligned with past findings and offered novel and nuanced insights into engineering inequity. The tool produced by this process was not only valid for this thesis investigation but could also be utilised in further research to establish greater understanding of engineering inequity. Finally, acknowledging that the model and instrument of engineering capital may yet be further improved a final set of analyses examined the tool in relation to other forms of capital for engineering and the engineering learning engagement of participants (see the Chapter Research Methods section of Chapter Eight for further details on this process). These analyses further validated the utility and relevance of the engineering capital instrument aligning it with other forms of engineering capital and applications within educational settings.

From May 2022 to December 2022 thesis writing continued to document these findings and outline the successful accomplishment of this thesis objective in the development of the engineering capital lens on engineering inequities in the UK.

Methodological Limitations

A number of limitations are present within this research methodology which impact its scope. First, the adoption of a questionnaire-based research design inherently introduced limitations to the collection of data and the depth of its insight. Questionnaires – particularly completed at a distance from researchers as in the case within this research – may be completed improperly leading to incomplete responses or dishonest/nonsense answers. A small number of such cases were present within this thesis dataset and were removed during data cleaning. Whilst this was mitigated through strong teacher guidance it nevertheless impacted the dataset and led to data loss. The questionnaire research design also carries inherent limitations to the depth of data it can access. This is particularly an issue with the use of closed questions, which prescribe the range of acceptable responses on offer to participants. This approach to data collection also removes the opportunity for a researcher to probe an answer further, as in qualitative designs such as interviews or focus groups, limiting the dimensions of detail within responses. Whilst the questionnaire adopted in this thesis was designed with these challenges in mind and addressed them with the inclusion of nested follow up questions the relative depth of insight is less than offered through qualitative methods. Unfortunately, in the context of the Covid-19 pandemic it was not feasible to undertake such qualitative methods to triangulate greater understanding alongside the use of questionnaires.

Second, the sampling method adopted through necessity within this research methodology is limited and likely affects how reliably the developed findings may be applied to wider audiences. The sample of 921 was relatively small in relation to all UK secondary school-aged learners. Whilst it would be impossible to recruit all secondary school-aged learners a random sampling technique would have supported greater reliability within the findings of this thesis. This was unfortunately not possible with the limited resources of a PhD project completed during a period of Covid-19 interruptions. However, attempts were made to build a representative sample where possible through geographic recruitment. Non-white ethnic groups were particularly poorly represented through this non-random recruitment. The time frame of this project did not allow for further targeted sampling to establish greater parity of ethnic representation. Despite this, analysis in Chapter Four suggests that the sampling of this thesis is consistent with past ethnically diverse samplings suggesting a degree of relative representativeness as a dataset. However, further research is necessary to confirm that the findings of this thesis apply to all young people across the UK. This further sampling is already required as an example of best practice in instrument development and should take particular care to investigate a wider array of ethnic groups.

A final limitation is the lack of triangulation within this research methodology to support greater credibility and validity to its conclusions. Triangulation refers to the process of drawing from multiple datasets or adopting multiple sources to build robust ‘triangulated’ understandings (Noble & Heale, 2013; Wilson, 2014). The employed methodology utilised only a single point of data collection through only a single data collection method. Triangulation was difficult within this research context: very little existing literature exists in relation to engineering inequity in the United Kingdom context from which to draw on, and the challenges of time and post-Covid-19 era limited the capacity to conduct qualitative follow up data collections. Early plans for this thesis included a later stage of focus groups and interviews in schools to build on insights provided by the empirical questionnaire but this was not possible during the Covid-19 pandemic. To mitigate this issue efforts were taken to develop rich conceptual and theoretical understandings that drew on wider literature, such as the science capital research literature, to triangulate the conceptual underpinning on the thesis data collection. If not triangulation through data, this offered triangulation of theory and a synthesis of ideas to meet the objective of advancing understanding of engineering inequities (Patton, 1999).

This methodology can therefore be seen to carry a number of limitations, that were mitigated where possible, but do influence the scope of this thesis and its findings. The objectives of this thesis were such that any development of understanding might represent success but the grander goal of supporting successful intervention of engineering inequities requires a larger collective effort and growing body of research literature. To that end, these limitations do not doom this work but offer opportunities to refine and build on the knowledge developed in this formative body of research.

Conclusions

This Methodology chapter has outlined the manner in which this thesis will accomplish its objective of developing greater understanding of engineering inequities in the United Kingdom. A conceptual framework was established to position the conceptualisation of engineering, inequity and the adopted Bourdieuian lens. A pragmatic research philosophy was adopted with a questionnaire-based, quantitative design to investigate the engineering capital of young learners. A procedure was outlined to first empirically test the relevance of the science capital model to engineering inequities before then developing a novel engineering-specific capital lens as a tool to better understand engineering inequities. The remaining chapters of this thesis will document this investigation and its resulting insights.

CHAPTER FOUR: TESTING SCIENCE CAPITAL FOR ENGINEERING INEQUITY

Introduction

Previously in this thesis, the theoretical model of science capital was critically examined to determine its relevance to the engineering domain. It was established that few of the constituent subcomponents of science capital are likely to apply to engineering in the same manner that they apply to science. This questioned the validity of adopting science capital within this thesis to investigate engineering inequity despite the noted utility of science capital. However, this theoretical analysis of science capital did recognise that the forms of capital contained within this model are likely relevant to engineering if approached in an engineering-specific manner and that an empirical analysis was necessary to confirm this critique. To that end, in Chapter Four the science capital model will be empirically investigated to determine its relevance to the engineering domain. A novel 'translation' of the science capital instrument which instead focuses on the engineering domain will also be investigated to determine the relevance of a similar engineering-specific approach. The science capital and 'Archer-style engineering capital' models will be comparatively applied to determine the value of these approaches to understanding engineering inequity. A further model of arts-based cultural capital will also be considered to frame this comparison in relation to the foundational capital perspective of Bourdieu. The comparison of these models will provide perspective on the validity of the science capital model to the engineering domain, the importance of adopting domain-specific models of capital in relation to inequity, and the continuing value offered by the Bourdieuian perspective. Drawing on the conclusions of previous chapters, it is expected that the Archer-style engineering capital model, as a domain-specific lens, will be better suited to understanding engineering inequities.

Empirically Investigating Science Capital and Engineering

The theoretical examination of science capital outlined in Chapter Two drew into question whether this innovative model could be adopted to effectively understand engineering inequities. Whilst the forms of Bourdieuian capital included in this model (such as literacy, attitudes and dispositions, talking to others) were likely to apply to the engineering domain, it was questioned whether a measurement of these capitals for science would be inclusive or reflective of capital held for engineering. This theoretical analysis concluded that science capital was unlikely to accurately reflect the engineering inequities present in the

UK but that an empirical analysis was necessary to confirm this hypothesis. The analysis also raised the possibility that an engineering-specific model of capital may outperform the science capital model warranting a comparative examination of the ability of science capital and a similarly structured engineering capital model to understand engineering inequities in the UK.

The notion that a subject-specific model of capital may outperform a more general model of capital is not unprecedented. The science capital model has previously been validated as a more effective lens on science inequity than a more general, high arts-based Bourdieuian cultural capital model (DeWitt et al., 2016). This study established that the science capital lens could explain greater variance in science inequity data than a traditional (and less context specific) Bourdieuian conceptualisation of cultural capital demonstrating the importance of specificity in the application of capital. It is thereby possible that an engineering-specific capital model would outperform the science capital model given the theoretical distinctiveness of engineering and science.

The comparisons of science capital and a general, high arts-based framing of Bourdieuian capital conducted by DeWitt et al. (2016) is also relevant to the investigation of engineering inequity. The arts-based, general cultural capital perspective was framed by Bourdieu as a model of social class based on the conceptualisation of taste, particularly around consumption of high art (Bourdieu, 1983; Bourdieu, 1984). Possessing the 'correct' tastes was understood as a social indicator that offered greater ease in integrating within the culture of education and social groups that hold power within society. As noted in Chapter One, the domain of engineering can be conceptualised as associated with the arts given the need for creativity in engineering problem solving, its use of design principles and physical materials which are also utilised in the practice of art (Cropley, 2016; Thompson & Lordan, 1999). In this way Bourdieu's original conceptualisation of cultural capital may apply to the engineering domain in a manner that does not for the science domain as demonstrated by DeWitt et al. (2016). The greater relevance of the general cultural capital lens – which was designed to comprehend social class differences – to the engineering domain is further supported by the acknowledgement that social class differences are greater in engineering than science (Friedman & Laurison, 2020). For these reasons it is relevant to also consider the relationship between Bourdieuian arts-based cultural capital and engineering inequities.

These analyses show that it is necessary to empirically consider the relevance of science capital, an engineering-specific model of capital, and arts-based cultural capital as lenses on engineering inequity. No such previous investigation is present within contemporary literature. In the following sections of this chapter three models will be compared: the science capital model, a similarly structured engineering-focused measure adapted from the science capital model (Archer-style engineering capital) and a Bourdieuian model of arts-based cultural capital. These will be empirically investigated and comparatively examined to establish their utility in building greater understanding of engineering inequities in the UK.

First, building on the theoretical analysis of Chapter Two, the differences between capitals for engineering and science will be explored to investigate the degree to which science capital might be generalised to the engineering domain. The distribution of capitals for engineering and science between groups will examine the alignment of these models to previously acknowledged patterns of engineering inequity. It is predicted that young people will possess different levels of capital for engineering and science validating the rejection of science capital and supporting the credibility of a novel engineering-specific model of capital.

Hypothesis One: Scores measured on the science capital instrument are predicted to significantly differ from scores on a similarly structured instrument of engineering capital.

Second, the three models of science, Archer-style engineering and arts-based cultural capital will be compared to determine their value as lenses on engineering inequity. The ability of each model to accurately predict engineering educational and career aspirations will be examined to determine the validity of each model as interpretative tools for engineering inequities. If a model of inequity cannot identify differences in aspirations for engineering then it is unlikely to aid the purpose of this thesis in developing understanding of engineering inequities within the UK. Recognising the importance of specificity in understanding patterns of inequity, it is predicted that the Archer-style engineering capital model will outperform science or general cultural capital models in identifying those young people who do or do not wish to engage with engineering in the future.

Hypothesis Two: An engineering-specific model of capital is predicted to hold greater power in explaining and predicting patterns of inequity in engineering educational and career aspiration compared to models of science or arts-based cultural capital.

Chapter Research Methods

Methodology

The fundamental aim of this chapter is to compare the ability of three models of capital to access and understand engineering inequities. Whilst not a replicative study it was essential that the models of science capital and art-based cultural capital were adopted as they have featured in past research, necessitating the adoption of an empirical quantitative research strategy. As outlined in the earlier Methodology chapter, this thesis has adopted a questionnaire research design to maximise the recruitment of participants. Data was collected from participants via a single point of collection through the completion of a research questionnaire featuring measurement instruments for science capital, Archer-style engineering capital and arts-based general cultural capital. These instruments could then be processed and analysed to answer the two hypotheses.

Participants

Data was collected from 921 secondary school-aged (11 to 16 years old) learners from ten schools in England and Scotland. As noted in the Methodology chapter, a single point of data collection was adopted for this thesis research project due to the demands of the Covid-19 pandemic. The sample of 921 learners examined in this chapter is the same sample examined throughout the thesis. See Methodology chapter for full outline of sample characteristics and rationale for the selected participant population.

Data Collection Instruments

Three instruments were included in the thesis questionnaire data collection to address these research questions: one each for science capital, Archer-style engineering capital and arts-based general cultural capital. Items were also included to assess engineering inequities and socioeconomic characteristics of participants. These instruments and items are outlined below and included within Appendix C and Appendix D.

Science capital instrument: The 14-item science capital instrument developed by Archer et al. (2015) was adopted to calculate science capital scores for participants. This instrument was adopted to facilitate a direct comparative measurement against previous findings in the science capital literature. The tool was initially developed through a process of data reduction and refinement from an broader set of items following Archer et al.'s theoretical model of science capital with items refined on the basis of their ability to discern young learners who did or did not aspire to science in their future (Archer et al., 2015). The resulting instrument is a strong measurement index that is theoretically and empirically validated for use in examining science inequity. The 14 items and their response scales are outlined in Table 4.01 below.

Table 4.01: Science capital instrument items and response scales.

Item	Response Scale
A science qualification can help you get many different types of job	-2 to 2 five-point Likert scale

When you are not in school, how often do you talk about science with other people?	0 to 4 five-point Likert scale
One or both of my parents think science is very interesting	-1 to 1 five-point Likert scale
One or both of my parents has explained to me that science is useful for my future	-1 to 1 five-point Likert scale
I know how to use scientific evidence to make an argument	-2 to 2 five-point Likert scale
How often do you go to an after-school science club?	0 to 4 five-point Likert scale
When not in school, how often do you read books/magazines about science?	0 to 4 five-point Likert scale
When not in school, how often do you go to a science centre, science museum, or planetarium?	0 to 4 five-point Likert scale
When not in school, how often do you visit a zoo or aquarium?	0 to 4 five-point Likert scale
My teachers have specifically encouraged me to continue with science after GCSE/National 5s	-2 to 2 five-point Likert scale
My teachers have explained to me that science is useful for my future	-2 to 2 five-point Likert scale
It is useful to know about science in my daily life	-1 to 1 five-point Likert scale
Who do you talk with about science?	0 to 3.5 scale based on number of contacts
Do you know anyone (family, friends, or community) that works as a scientist or in a job that uses science?	0 to 7 scale based on number of contacts

A single science capital score was calculated for each participant by totalling the scores for the 14 items which was then transformed to produce a score on a scale from 0 to 105 as per previous literature[1]. A Cronbach's Alpha analysis was conducted to test the internal consistency of responses within the thesis dataset and confirmed the previously established reliability of this measurement instrument (N=854, Alpha based on standardised items= 0.851).

Archer-style engineering capital instrument: It was essential that the engineering capital measurement instrument adopted for comparison with science capital was closely controlled as not to introduce extraneous variables that would invalidate the focal comparison between science and engineering domains. It was therefore necessary to measure the same forms of capital in each measurement instrument, utilising the same language and empirical approach. To accomplish this the 14-item science capital instrument was 'translated' to replace framings of science with framings of engineering. The resulting instrument was titled 'Archer-style engineering capital' in reference to its close alignment to Archer et al.'s science capital instrument (Archer et al., 2015). The Archer-style engineering capital

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[1] This transformation was calculated with the following equation: 2(SCORE)+22.

measurement tool measured the same forms of capital as the science capital instrument, with the same response scales, and very similar item phrasing to control extraneous variables and maximise the focus of the study on the differing domains of science or engineering. The point of difference between the measurement tools of science capital and Archer-style engineering capital related only to the STEM domain. The outline of the source science capital items and their translations are outlined below in Table 4.02.

Table 4.02: Science capital instrument items and 'translations' to form the Archer-style engineering capital instrument with response scales.

Science Capital Items	**Translation to Archer-Style Engineering Capital Item (changes emboldened)**	**Response Scale**
A science qualification can help you get many different types of job	**An engineering** qualification can help you to get many different types of job	-2 to 2 five-point Likert scale
When you are not in school, how often do you talk about science with other people?	When you are not in school, how often do you talk about **engineering** with other people?	0 to 4 five-point Likert scale
One or both of my parents think science is very interesting	One or both of my parents think **engineering** is very interesting	-1 to 1 five-point Likert scale
One or both of my parents has explained to me that science is useful for my future	One or both of my parents has explained to me that **engineering** is useful for my future	-1 to 1 five-point Likert scale
I know how to use scientific evidence to make an argument	I know how to **design and make things**	-2 to 2 five-point Likert scale
How often do you go to an after-school science club?	How often do you go to an after-school **club that involves engineering**?	0 to 4 five-point Likert scale
When not in school, how often do you read books/magazines about science?	When not in school, how often do you read books/magazines about **engineering**?	0 to 4 five-point Likert scale
When not in school, how often do you go to a science centre, science museum, or planetarium?	When not in school, how often do you go to a science centre, science museum, or planetarium?	0 to 4 five-point Likert scale
When not in school, how often do you visit a zoo or aquarium?	-	0 to 4 five-point Likert scale

My teachers have specifically encouraged me to continue with science after GCSE/National 5s	My teachers have specifically encouraged me to **consider studying engineering** after GCSE/National 5s	-2 to 2 five-point Likert scale
My teachers have explained to me that science is useful for my future	My teachers have explained to me that **understanding engineering** is useful for my future	-2 to 2 five-point Likert scale
It is useful to know about science in my daily life	It is useful to know about **engineering** in my daily life	-1 to 1 five-point Likert scale
Who do you talk with about science?	Who do you talk with about **engineering**?	0 to **4** scale based on number of contacts
Do you know anyone (family, friends, or community) that works as a scientist or in a job that uses science?	Do you know anyone (family, friends, or community) that works as **an engineer** or in a job that uses **engineering**?	0 to 7 scale based on number of contacts

Most items on the science capital instrument could be translated directly with simple word replacements for ‘science’ or ‘scientist’ to ‘engineering’ or ‘engineer’, however some slight adjustments were necessary to ensure relevance of the items. The item “I know how to use scientific evidence to make an argument” was adjusted to “I know how to design or make things”. This item was judged to examine a key practice central to the activity of science from the perspective of a secondary school-aged participant, and so a comparable key practice of engineering was chosen as its replacement. The scale for the question “Who do you talk with about engineering?” was also modified adding a further potential response of ‘directly with engineers’ adding a further 0.5 to the scale of possible scores for this question. The item “When not in school, how often do you go to a science centre, science museum, or planetarium?” was not changed as this question was judged to already apply to engineering given the presence of engineering-based learning in these contexts. One science capital item, “When not in school, how often do you visit a zoo or aquarium?”, could not be translated as there was not determined to be a directly parallel learning context specific to engineering that may be encountered by young people in the manner in which they may encounter a zoo or aquarium. Whilst it may have been possible to find an example of such an engineering-specific informal learning context it was judged that this would not be directly comparable to visiting zoos or aquaria. Instead, it was decided that the item would be removed and that the calculation to place the instrument score onto a comparable 0-105 scale would be adjusted to facilitate this change in instrument range.

Totalling scores from these 13 items resulted in a range from -11 to 38, which was transformed for ease of comprehension and comparison with the science capital instrument to a scale of 0-105[2]. A Cronbach's Alpha analysis was conducted to test the internal consistency of responses within the thesis dataset; this test confirmed the internal consistency of the Archer-style engineering capital instrument (N=846, Alpha based on standardised items = 0.840).

Arts-based, general cultural capital instrument: A six-item measure of general cultural capital was adopted from Archer et al.'s previous literature to facilitate a comparison between newer models of capital such as science capital and the traditional Bourdieuian conceptualisation of cultural capital. The forms of capital included in this measure are consistent with many past empirical applications of Bourdieuian cultural capital (De Graff et al., 2000; Stopforth & Gayle, 2022). Four items explored parental education level, which from a Bourdieuian perspective can be seen as linked to societal position and socialisation of next generations (Bourdieu & Passeron, 1977). Parental education level is long recognised as linked with intergenerational patterns of inequity beyond the Bourdieuian perspective (Lareau, 2011; Shavit & Blossfeld, 1993) The scale also contained items relating to access to reading materials in the home and participation with informal learning contexts which a Bourdieuian perspective would also position as societally stratified as socialised behaviour (Bourdieu, 1984). Reading materials and participation with informal learning are also more widely recognised in relation to inequity (Breinholt & Jaeger, 2020). The six-item scale is outlined in Table 4.03 below.

Table 4.03: General cultural capital items and response scales.

Item	Response Scale
Did your mother leave school before age 16?	-1 to 1 three-point Likert scale
Did your mother go to university?	-1 to 1 three-point Likert scale
Did your father leave school before age 16?	-1 to 1 three-point Likert scale
Did your father go to university?	-1 to 1 three-point Likert scale
Approximately how many books, including e-books, are there in your home?	0 to 2 five-point Likert scale

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[2] This transformation was calculated with the following equation: 2.1428571428571(SCORE)+23.57142857142. The calculation adjusted for the slight increase in range for the question "Who do you talk with about engineering?" and removal of the item "When not in school how often do you visit a zoo or aquarium". This slightly decreases the value of each point on the 0-105 scale for Archer-style engineering capital compared to science capital but this decrease is negligible and unlikely to influence the comparison of measurements. A 1 unit increase on the scale of 0-105 is equal to: +0.5 for science capital, and +0.466666 for Archer-style engineering capital resulting in a total difference per unit of 0.033333. This was judged to be a reasonable measurement difference, particularly as scores on both measurement instruments were expected to skew to the lower end of the scale limiting the effect of an aggregating point difference.

How often do you do the following things when you are not in school: go to a museum?	0 to 2 five-point Likert scale

Totalling scores of these items resulted in a range from -4 to 8. A Cronbach's Alpha analysis was conducted to test the internal consistency of responses within the thesis dataset; this test identified only a moderate internal consistency of responses to these items that questioned the reliability of this instrument (N=889, a=0.575 based on standardised items). Despite the lower levels of reliability indicated by this test the scale will be used as designed to enable comparison with previous uses of this model by Archer et al. and others in exploring general cultural capital and to facilitate a direct examination of the traditional Bourdieuian framework. The lesser relevance of traditional cultural capital to modern contexts is acknowledged in literature but lacks a consensus on the implications of this in application (Breinholt & Jaeger, 2020; Stopforth & Gayle, 2022).

Engineering inequity:

In order to examine how well the three models of capital relate to patterns of engineering inequity it was necessary to establish a dependent variable measure of engineering inequity within the sample population. To empirically examine engineering educational and career aspiration, two items were included in the questionnaire. To assess engineering educational aspiration an item asked participants whether they wished to study engineering following their secondary education ("Although it is a long way off, which of the following describes your views: I would like to study engineering at university, at college/sixth form, after GCSE/National 5s but not A-Level/Highers, I do not want to study any engineering after GCSE/National 5s, None of the above or I don't know"). To assess engineering career aspiration participant interest in engineering careers was established ("Do you think you might like to work in an engineering-related job in the future? Yes, No").

Sample characteristics: Participants were asked to report their current year of schooling to determine their progression through the education system and age ("What year group are you in?"). Participants were asked to provide a gender identity to facilitate an examination of capitals for science and engineering by gender grouping given the recognised gender inequities within UK engineering ("Are you a girl or boy? Girl, Boy, Other Identity"). Respondents were also asked to provide their ethnic identity to examine potential distinctions in capital amongst differing ethnic groups in response to recognised inequities in ethnic representation in UK engineering ("What of the following best describes your ethnic origin?").

Respondents were also asked to name their school allowing an examination of geographical distribution of the sample ("What is the name of your school?").

The complete questionnaire is available in Appendix C.

As past literature had identified that UK professional engineers skewed towards greater socioeconomic privilege it became necessary to consider the social class of participants (EngineeringUK, 2018b; Friedman et al., 2015; Friedman & Laurison, 2020). This was measured in two ways, as outlined in the Methodology chapter, drawing on a measure of cultural capital and positioning with the Income Deprivation Affecting Children Index (IDACI) sub-index of the Indices of Multiple Deprivation (IMD) measure.

It was not possible to examine the secondary school-aged participants in relation to academic ability for engineering as this is not a curricular subject for most learners in the UK. Instead, academic ability in the science domain was examined through questioning which academic set the participant belonged to for science classes ("Which of the following statement below is true for you now? I am in one of the top sets, middle sets, bottom sets, there are not sets in my school."). This was deemed valid given the 'science first, engineering later' structure of the education system aligns the science learning of secondary school-aged learners with later engineering study. This question allowed capitals for science and engineering to be examined in relation to academic ability which is a valid consideration for science capital as established in previous literature which found that those with high science capital skewed to higher science academic ability (Archer et al., 2015).

Procedure

The questionnaire instrument was designed, developed, and applied for data collection as outlined in the Methodology chapter. Following data processing and cleaning the thesis dataset was examined to analyse the two hypotheses outlined in this chapter.

For hypothesis one, this analysis involved the application of mean comparison testing to determine the relationship between scores on the science capital and Archer-style engineering capital instruments. A paired samples t-test was confirmed as appropriate through the testing of statistical assumptions. A paired samples t-test is acknowledged as an appropriate test to compare the means score of two instruments completed by the same participants (Ho, 2013). To examine the distribution of science and Archer-style engineering capital scores between groups (based on gender, social class, science ability and national context) frequency analysis, independent samples t-tests and one-way ANOVA analyses were adopted to examine the difference in capital scores. These tests were also confirmed as appropriate through validation of test assumptions (see Appendix E). Tests such as these are appropriate for the comparison of distribution and means between independent groups (Ho, 2013).

For hypothesis two, binary logistic regression analyses were adopted to examine the predictive power of the science capital, Archer-style engineering capital and arts-based, general cultural capital models in understanding engineering educational and career inequities. This test was chosen for its ability to examine the ability of models to correctly classify individuals in relation to their aspirations. The ability to clearly reduce aspirations for engineering to a binary yes/no response supported the use of binary logistic regression over other regression approaches (Ho, 2013). The adoption of these tests was confirmed as appropriate through validation of test assumptions (see Appendix E).

Results and Discussion – Hypothesis One

Hypothesis One: Scores measured on the science capital instrument are predicted to significantly differ from scores on a similarly structured instrument of engineering capital.

Comparing Science Capital and Archer-Style Engineering Capital

A Pearson's correlation analysis was adopted to examine the association between scores on the science capital and Archer-style engineering capital instruments. A paired samples t-test was also adopted to investigate the degree to which participant scores on the science capital and Archer-style engineering capital indices differed. The correlational analysis identified a significant positive moderate association between scores on the two instruments ($r = 0.556$, $N=921$, $p<0.001$). The paired samples t-test found a significant difference between science capital and Archer-style engineering capital scores ($t(920) = 16.848$, $p<0.001$, $d=0.555$), with mean science capital scores ($M=41.34$, $SD=14.04$) found to be significantly higher than mean Archer-style engineering capital scores ($M=34.13$, $SD=13.50$). The Cohen's d score of 0.555 indicates a medium strength effect size of this change in the STEM domain (see Appendix E for statistical outputs).

These findings confirm the prediction of hypothesis one and the theoretical critique of science capital outlined in Chapter Two by establishing that capitals for science and engineering are not the same amongst young UK learners. Whilst the correlational analysis identifies a positive relationship between scores on the two instruments the moderate strength of this dynamic ($r=0.556$) highlights that these scores are not wholly the same. As argued in Chapter One, science and engineering do share some commonalities in a 'family resemblance' manner which may explain this association. However as also argued in Chapter One, an association between these domains does not mean that they are identical or operate similarly in relation to their distinct patterns of inequity. The Archer-style engineering capital model – which includes the same forms of capital, very similar questionnaire items, and was measured with the same sample at the same time – calculated a different level of capital for engineering than the science capital model calculated for science. This clearly validates that science capital is not the same as capital for engineering. The higher mean scores for the science capital model (M=41.34 compared to M=34.13 for the engineering capital model) demonstrate that the use of science capital to comprehend engineering inequity would overestimate the volume of supportive capital held by young people for engineering. This challenges the usage of science capital as a 'STEM capital' model or for efforts to understand engineering inequity.

Investigating the Distributions of Science Capital and Archer-Style Engineering Capital

Having established that capitals for science and engineering differ amongst young UK learners it is next possible to examine the distribution of these capitals to establish how the identified differences relate to socioeconomic groups. Whilst the analysis of overall mean scores for science and engineering capital statistically differ it may be that some socioeconomic groups possess more similar or dissimilar levels of engineering and science capital. As a result, it may be that science capital is representative of engineering inequity for some but not others. Understanding who possess science capital aligned to their capitals for engineering offers insight into who benefits from assumptions that science and engineering are the same. Examining the distributions of capital for engineering also provides the opportunity to explore the distribution of these supportive, advantageous resources across differing socioeconomic groups to illuminate patterns of engineering inequity that are only simplistically understood in the UK context.

The Distribution of Science and Engineering Capitals

A frequency analysis was utilised to consider the strength of capitals for science and engineering across the population of secondary school-aged learners. The examination of distribution of capitals for science and engineering can provide an overview of support for science and engineering within this population. Participants were classified according to their score for science and engineering capital into low (0-34), medium (35-69) and high (70-105) capital groups. This structure also facilitated examination against past science capital literature which also utilised this structure to categorise participants based on their science capital score (Archer et al., 2015; Moote et al., 2021).

The frequency analysis revealed that science capital is more broadly distributed in the secondary school-aged population than Archer-style engineering capital. Of those sampled, 33.8% possessed a low amount of science capital, whereas a 62.5% majority possessed medium science capital and 3.7% possessed a high volume of science capital. These distributions are comparable to previously published distributions of science capital validating the sampling of this thesis; in particular, the science capital distribution of this thesis sample is similar to DeWitt et al.'s (2016) targeted sample which was designed to overrepresent those from non-white ethnicities suggesting that the thesis sample is representative of wider ethic groups despite lacking a broad ethnic diversity. Table 4.04 outlines the distribution of thesis science capital and Archer-style engineering capital measurement in comparison with previously published distributions of science capital.

Table 4.04: The distribution of science capital and Archer-style engineering capital amongst three groups (low, medium, high capital scores) in past literature and this thesis sample.

	Previous Literature			**Thesis Dataset**	
Level of Capital	Archer et al. (2015) - Science Capital Distribution	DeWitt et al. (2016) - Science Capital Distribution	Moote et al. (2021) - Science Capital Distribution	Thesis - Science Capital Distribution	Thesis - Archer-style Engineering Capital Distribution
High	5%	4.9%	4.9%	3.7%	1%
Medium	68%	66.9%	62.4%	62.5%	42%
Low	27%	28.3%	32.6%	33.8%	57%

The frequency analysis of Archer-style engineering capital reveals that the sample possessed less capital for engineering than science, with 57% in the low capital group, 42% in the medium group, and only 1% in the high capital group for engineering. This differs from both the distribution of science capital in previous studies and the science capital scores within this thesis dataset. Overwhelmingly this difference represents a move towards the 'low' capital group, with 20.5% fewer participants in the medium group for engineering compared to science, and 2.7% fewer in the high capital group. This distribution demonstrates that secondary school students possess less engineering capital than science capital and this deficit sees the majority of participants positioned into a 'low' level of engineering capital.

These findings put into focus the relative paucity of supportive engineering capital held by secondary school learners. This lesser presence of capital for engineering across the population shows that young people are less supported with advantageous resources for engineering compared to science. This contributes to our understanding of why engineering engagement in the UK context is poor and how the engineering skills shortages facing the UK are so longstanding. As the Archer-style engineering capital model is a more specific measure of capital for engineering than science capital these findings represent a novel insight into the degree of support for engineering amongst UK secondary school learners. The distinctiveness of patterns of distribution of science and engineering capital further confirms our hypothesis that an engineering-specific approach to engineering inequity is more appropriate than an approach that generalises from science. Such a generalisation, or adoption of science capital to understand engineering inequity, would not represent the true resources for engineering present within the population of young UK learners. This further validates the need for an engineering-specific approach to inequity in the UK.

Gender Differences in Science Capital and Archer-Style Engineering Capital

As noted in Chapter One, gender differences contribute greatly to the inequitable participation with engineering found within the UK where only 16.5% of engineers are women (EngineeringUK, 2022b). Whilst gender-based inequities are present throughout the STEM grouping, including science, the differences in participation and representation within engineering are stronger in engineering with a greater skew to males (WISE, 2014). As a result, it might be questioned how well science capital can represent engineering given the domain of engineering carries distinct patterns of gendered participation – both STEM domains are skewed towards male representation but skew in differing degrees. To investigate this two independent samples Welch's t-tests were conducted to examine gender differences in science capital and Archer-style engineering capital indices.

The first Welch's t-test revealed no significant difference in science capital score by gender group (t(820.578) = -0.697, p=0.486, d=-0.047[3]) with the mean science capital scores of girls (M=41.59, SD=13.83) and boys (M=40.93, SD=14.23) not differing significantly. However, the second Welch's t-test revealed a significant difference in Archer-style engineering capital score by gender group (t(754.347) =

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[3] The Cohen's d effect size calculation was adjusted to apply to the Welch's t-test calculation. An unadjusted Cohen's d utilises the pooled standard deviation of both groups. This is incompatible with groups that lack a homogeneity of variance. Alternative tests are also incompatible: a Hedges' g calculation also requires homogeneity of variance and Glass' d is only valid in control vs. experimental group comparisons. The Cohen's d was instead adjusted to minimise the impact of differing variances. Rather than pooling the standard deviation of the two groups, the average of the combined standard deviations (i.e. square root of the average of their variances) was instead utilised to develop control between groups. The adjusted Cohen's d calculation: Cohen's d= (Mean Value Group A – Mean Value Group B)/ √((Variance Group A + Variance Group B)/2). This calculation is used for all Welch's t-test Cohen's d reports within this thesis.

4.797, p<0.001, d=0.323) with boys mean Archer-style engineering capital score (M=36.72, SD=14.55) significantly greater than the mean scores for girls (M=32.30, SD=12.31). The Cohen's d effect size indicates a small-medium effect size of gender on discerning Archer-style engineering capital score highlighting the influence of gender in capitals for engineering (see Appendix E for statistical outputs).

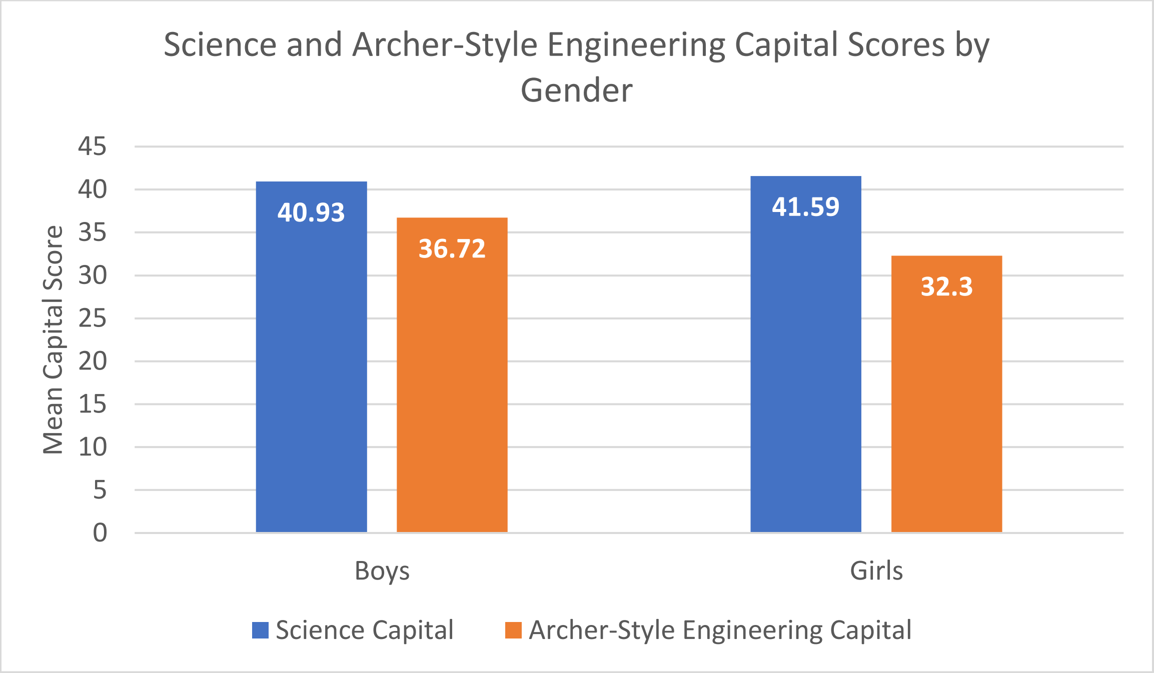

Figure 4.01: Mean science and Archer-style engineering capital score by gender.

These findings are noteworthy on several counts. First, and most importantly, these findings demonstrate that the patterned distribution of capitals for science and engineering differ by gender group. Whereas the science capital model would suggest that the boys and girls in this sample do not significantly differ in their provision of supportive capital, the Archer-style engineering capital model does identify a statistically significant difference with girls possessing significantly less capital for engineering than boys. This suggests that the science capital model is not sensitive enough to detect these differences in resourcing for the engineering domain. This is critically important given the centrality of gender to issues of engineering inequity. If science capital was deployed to understand engineering inequity its measurement would not reflect the acknowledged lack of representation of women. This comparative examination validates that the nuance and specificity of engineering is not well represented within the science capital model and instrument and as a result the distinct engineering-specific approach proposed in this thesis is appropriate.

Secondly, this analysis highlights that girls possess particularly lower levels of capital for engineering than science. Where boys have a mean difference of 4.21 between their science and engineering capital scores for girls this is much greater with a mean difference of 9.29. This contributes to an understanding of how engineering inequity manifests, highlighting that the bridge between science and engineering is generally wider for girls than boys. This insight must inform pedagogical strategies to address inequities and shows that STEM-integrated approaches that introduce engineering into existing curricular structures for science may carry a differential difficulty or value favouring boys (Roehrig et al., 2021, Roehrig et al., 2021a). In this way, a well-intentioned intervention to address inequity may in fact deepen disparity if the differential levels of resource for engineering amongst gender groups are not considered. These findings demonstrate that an adoption of science capital to understand engineering inequity would favour boys and greatly miscomprehend the supportive engineering resource possessed by girls. These findings further show the value of an engineering-specific lens on capital given that the use of science capital would not identify this complex interaction between inequity in STEM domains and gender.

Finally, this data also differs from previous measurements of science capital which did find statistically significant differences in science capital by gender. Where Archer et al. (2015) and Moote et al. (2021) find significant differences in science capital by gender, with boys possessing significantly more science capital, the thesis dataset does not find this. These differences are outlined in Table 4.05 below.

Table 4.05: Gender difference analysis for science capital in past literature and thesis dataset.

	Previous Literature		**Thesis Dataset**	
Gender	Archer et al. (2015) - Science Capital Mean Scores	Moote et al. (2021) - Science Capital Mean Scores	Science Capital Mean Scores	Archer-style Engineering Capital Mean Scores
Boys	43.16	42.27	40.93	36.72
Girls	39.61	40.99	41.59	32.30
Significant Differences by Gender	***Yes***	***Yes***	***No***	***Yes***

No such difference was identified within this thesis dataset. The absence of this gendered difference is less likely to be explained by sampling given that the general distribution of science capital mirrors previous samples as outlined in Table 4.04 and gendered differences for engineering are identified suggesting the sample is sensitive to gendered differences to some degree. The high significance level of the Welch's t-test identifying no difference in science capital by gender (p=0.485) shows that this is not a borderline finding. This finding would therefore suggest a change from earlier statistically significant findings in gendered difference for science capital. Whilst further investigation is necessary it may be that in the UK context girls now possess greater parity in science capital compared to earlier samples reported in 2015 or 2019. This is plausible given the introduction and widespread adoption of the science capital perspective, including the Science Capital Teaching Approach, which operate with the objective of lessening inequities in science. The lack of significant difference in science capital scores for boys and girls within this sample could represent an increase by girls of the sorts of science capital included in this measurement (e.g. participation with informal learning contexts such as zoos, aquaria or science museums; consumption of science media; or teacher encouragement for science education and its value). With hindsight this change may be observable in past science capital literature: no effect size for the gendered effect was given in the formative science capital literature (Archer et al., 2015) and a later study only identified a small effect of gender on science capital scores (Cohen's d = 0.16 and 0.2 in Moote et al. (2021)). Further examination of this finding is warranted to determine the ongoing sensitivity of science capital and evolving inequities within the UK science domain.

These analyses of gender and capital further support the prediction of hypothesis one that an engineering-specific model of capital would outperform a generalised perspective of science capital on engineering inequities in the UK.

Science Academic Ability Differences in Science Capital and Archer-style Engineering Capital

Little past research has considered the intersection of academic ability in science or engineering and patterns of engineering inequity; however, this consideration is relevant given the 'science first, engineering later' structure to STEM education in the UK. The relationship between science ability and engineering participation and representation is institutionally enforced with science qualifications often necessary to access engineering educational pathways. Considering this the ability to achieve and qualify in the science domain becomes relevant to the topic of engineering inequity. To explore the degree capitals for science or engineering may relate to science academic ability of young learners two one-way ANOVAs were deployed to explore how science capital or Archer-style engineering capital scores differed by low, medium, or high science academic ability sets. 'No science sets' were also considered in schools that did not adopt this hierarchy.

The first one-way ANOVA revealed a significant difference in science capital score by academic set for science (F(3,893) = 29.16, $p<0.001$, $ETA^2=0.089$) with those in higher sets (M=45.84, SD=13.83) possessing significantly more science capital than those in medium (M=36.27, SD=12.33), lower (M=36.92, SD=14.71) and no science sets (M=40.56, SD=13.97) groups (see Appendix E for statistical outputs). Whilst only a minor effect size this does demonstrate that science capital is aggregated more in those who have an academic ability with science. The same finding is established in Archer et al.'s formative science capital work (Archer et al., 2015) and later explorations of science capital within the UK (Moote et al., 2021). This replication of past findings further supports the reliability of the science capital measurement within this thesis and highlights the importance of diversions from expected findings such as in the lack of gendered difference in science capital scores.

The second one-way ANOVA explored how Archer-style engineering capital differed between the same four academic groups and found a significant difference (F(3,893) = 3.367, p=0.018, $ETA^2=0.011$), however unlike with science capital the only significant difference between academic groups for engineering capital was between higher science sets (M=35.06, SD=13.61) and middle science sets (M=31.92, SD=13.89). Those in lower (M=35.54, SD=13.69) and no science set (M=34.98, SD=12.73) groups did not differ significantly from the higher sets (see Appendix E for statistical outputs).

It should be noted that the sample for those in lower science sets was particularly small (N=48, 5.2%) and should therefore be considered as suggestive rather than indicative – further examination is warranted.

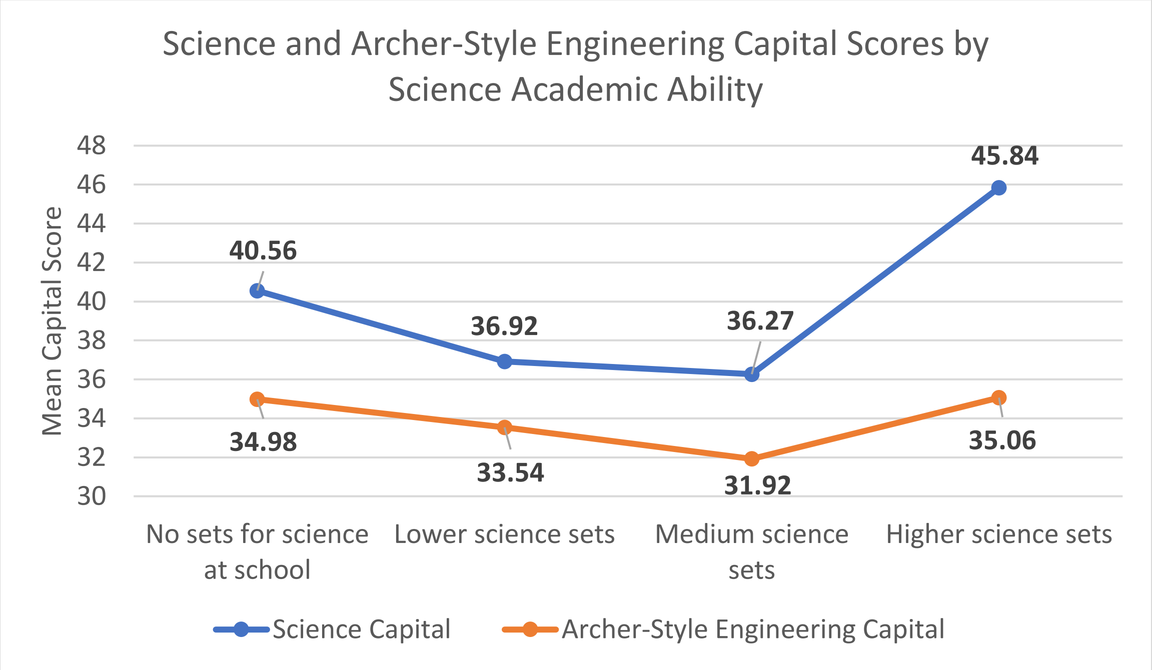

Figure 4.02: Science and Archer-style engineering capital scores by science academic ability.

These findings further highlight that capitals for science and engineering are differentially distributed, in this case by the social grouping of academic science ability. If sets for science are taken as a general indicator of academic ability for science then this would suggest a difference in how capitals for science and engineering relate to academic ability and resulting school experiences. For science capital there is a clearer hierarchy with those in top sets demonstrating the greatest science capital, however this hierarchy is less clear in measurements of Archer-style engineering capital where those in higher and lower science sets possess remarkably similar levels of Archer-style engineering capital. This further highlights the distinction of capitals for science and engineering, but also challenges the conceptualisation of engineering as a form of science or science-like. This nuance for engineering would not be identified through the use of science capital, instead it would be assumed that those in high ability sets possessed greater resource for engineering than they do and those in low ability sets would not be recognised as just as supported for engineering as more science academically able peers. If the use of these models of inequity are concerned with identifying and supporting future engineers then the engineering capital model clearly outperforms science capital in its value to understanding preparedness for the study of engineering. Given that the examined sample are secondary school students who are poised to make decisions that will align them towards or away from engineering the ability of an engineering-specific lens to recognise these distinctions is of high value and utility.

This difference in distribution of capitals for science and engineering also offers an interesting perspective on the dominant ‘science first, engineering later’ structure of UK education systems. Within these conventional systems it may be perceived that those in high science academic sets are best placed to move into subsequent stages of education for engineering, however the analysis outlined above would suggest that those in lower ability science sets may also possess comparable levels of supportive capital for engineering. These individuals may represent an untapped resource of potential future engineers – or, alternatively, this might be interpreted as those in high academic science sets possessing no greater capital for engineering than those in lower sets. This is relevant to debates around the definition of ‘engineer’ and its relationship with ‘technician’ roles which are understood as a duality within engineering professions (Department for Business Innovation and Skills, 2013). These findings may also represent a pattern of embodiment that validates the duality of vocational or academic routes into the engineering domain. Given unequal sample sizes this understanding of the relationship between engineering capital and science ability requires further examination. As elsewhere in this analysis, these findings demonstrate that presuming science capital is the same as, or representative of, engineering capital would result in an inaccurate perception of capitals for engineering.

Deprivation Group Differences in Science Capital and Archer-Style Engineering Capital

Social background and relative deprivation are also relevant considerations for engineering inequity given the identification that engineers in the UK are skewed to origins of greater socio-economic privilege (EngineeringUK, 2018b). Social class, which might be framed as degrees of relative deprivation or advantage, is therefore an important consideration to which a model of engineering inequity must respond. The impact of class/deprivation likely differs for science and engineering, recognising that within the UK engineering is likely more inequitable than science (Friedman & Laurison, 2020). This immediately draws into question the ability of science capital to represent both science and engineering with a single score given the strong link between social class and the underlying Bourdieuian concept of capital.

As noted in the earlier Methodology chapter, the measurement of social class is made difficult by its potential framing in either economic or social terms. To ensure a suitably sophisticated examination of social class the distribution of science capital and Archer-style engineering capital were considered in relation to both a social measure (Bourdieuian cultural capital for class) and an economic measure of social class (the Income Deprivation Affecting Children Index, IDACI). The use of cultural capital can facilitate a direct comparison with Archer et al. (2015) who utilised this approach, but the IDACI can facilitate a more contemporary economic approach to framing deprivation. This facilitates a richer examination of how science capital and Archer-style engineering capital relate to deprivation as a relevant characteristic of engineering participation and inequity issues in the UK.

For the cultural capital assessment of social class/deprivation, a one-way ANOVA revealed significant differences in science capital for groups with differing cultural capital ($F(4,916) = 40.659$, $p<0.001$, $ETA^2=0.151$) with significantly greater science capital as cultural capital increased except for between the Very Low and Low, and Very Low and Medium levels (see Appendix E for statistical outputs). Overall, this finding demonstrates that individuals belonging to families with greater cultural capital (indicative of higher classes or lesser deprivation) also generally have more science capital. This mirrors Archer et al.'s (2015) findings on the distribution of science capital within different cultural capital groups, further validating the measurement of science capital in this thesis to previously reported measures in wider literature.

A second one-way ANOVA revealed a significant relationship between Archer-style engineering capital and general cultural capital ($F(4,916) = 8.511$, $p<0.001$, $ETA^2=0.036$) with a number of significant distinctions in engineering capital between differing cultural capital groups . However, unlike with the first one-way ANOVA exploring science capital, the linearity of this relationship was less clear. No significant differences were found to exist between the Very Low and other levels of general cultural capital, and no difference was found between the Medium and High, or High and Very High levels (see Appendix E for statistical outputs). As a result, it may be that engineering capital is less clearly distinguished between cultural capital groups. The same upward trend is observed, but distinctions are less clear within this trend.

These findings further demonstrate the difference between science and engineering capitals, highlighting that the two relate to the cultural capital measurement of social background in somewhat distinct patterns. Whilst both models show a positive trend to social background these patterns cannot be seen to be identical with differing ETA^2 effect size values highlighting a differing level of importance between social background and the two STEM domains. This questions whether the science capital model can be representative of engineering. Given that Bourdieuian cultural capital is the foundational framework of both the science capital and Archer-style engineering capital measures the difference in relationships with this core concept further questions the presumption that science capital is inclusive or representative of engineering. These findings suggest that science is more closely aligned to social class/privilege than engineering. This may be interpreted as resulting from differences in parental approaches to supporting education. The Bourdieuian framework positions parent-child relations as deeply influential in the development of habitus (Bourdieu, 1984) but also the in shaping of parenting style with those with greater capital able to pass down forms of capital that support learners in the institution of education, which itself is aligned to the capital of the powerful (Lareau, 2011). This is confirmed in further research with parents from more privileged backgrounds approaching child learning differently from those in lower class groups (Gerris et al., 1997; Kohn, 1977) – though others propose alternative interpretations beyond class structure for these differences (Chan & Koo, 2011). As science is in the curriculum it may be the recipient of this beneficial influence from privileged parents. However, as engineering is absent from this education system it may not be the subject of additional support. Alternatively, these patterned findings may be explained by an understanding of engineering as a duality, practiced both by white collar, highly educated professional engineers and blue collar, less educated engineering technicians. As a result, parents in both groups may be well placed to nurture capital amongst their children. Further research is required to explore these interpretations.

Social class can also be considered with a more economic lens by utilising the Index of Multiple Deprivation (IMD) sub-index of Income Deprivation Affecting Children Index (IDACI). Two one-way ANOVA analyses were utilised to examine the relationship between quintiles on the IDACI measure and science capital and Archer-style engineering capital scores. The first one-way ANOVA revealed no significant difference in the level of science capital by IDACI quintiles (F(4,601) = 0.176, p=0.951, ETA^2=0.001). Very little variation is noted, with all five quintiles reporting mean science capital scores in the range 41.21 to 42.69 (range: 1.48) (see Appendix E for statistical outputs). The second one-way ANOVA also found no significant difference in the level of Archer-style engineering capital by IDACI quintile (F(4,601) = 0.340, p=0.851, ETA^2=0.002). As with science capital, Archer-style engineering capital barely differed between quintiles with a range of means of 33.24 to 34.99 (range: 1.75) (see Appendix E for statistical outputs).

The lack of significant relationships between the models of science capital and Archer-style engineering capital and the IDACI measure of deprivation are insightful for a number of reasons. First, the lack of significant findings challenge the notion that these models are effective models of inequity given that economic disparity is a foundational characteristic of social disparity. This would also challenge the idea that economic capital can facilitate the development of capitals for science and engineering as noted in previous literature, such as the dominance of more economically privileged individuals in UK informal science contexts (Canovan, 2020; Kennedy et al., 2018).

Second, these findings demonstrate that the methodological approach to measuring social class is of great importance and influence on resulting findings. The use of a more social, general cultural capital measurement of social disparity resulted in significant differences in science and Archer-style engineering capital scores, yet no difference in these same scores were identified when utilising a strictly economic framing of disparity. This suggests that the distinctions in science and engineering capitals are determined by social, not economic, factors. This would not be surprising given that it is cultural and social capitals, and not economic capitals, that make up the content of these perspectives and models. Whilst a relationship may exist between differing economic groups the above findings suggest that this would be due to the social differences. This does align to past findings examining social or economic measures of social class which are noted to produce distinct conceptualisations and measurements of disparity (Bukodi & Goldthorpe, 2013; Chevalier & Lanot, 2002). These findings should be further investigated with greater depth in the measurement of economic and social-based deprivation to confirm the relationship between engineering capital and deprivation. A qualitative investigation as well as broader quantitative examination of social class/economic disparity and engineering inequity is warranted. The adoption of a more accurate measure of economic disparity than the IDACI, which depends on generalisations according to postcode, is also needed as it may be that patterns of engineering inequity are not geographically determined (and so cannot be examined using the postcode generalising IDACI instrument).

National Differences in Science Capital and Archer-Style Engineering Capital

Despite engineering inequities often being discussed as a UK-wide issue it is important to note that the UK features four devolved governments which influence policy in distinct manners. For example, the UK contains devolved approaches to education which limit degree to which educational experiences can be generalised for all UK learners. This diversity of educational policies, practices and structures is relevant to the consideration of engineering and science capital given the recognised importance of education in shaping inequities (Munoz & Dossett, 2001). However, the data used in the formation, measurement and development of science capital was sourced solely from an English context (Archer et al., 2015). This might be seen to limit the scope of science capital and question its ability to act as a model of science inequity for the whole of the UK beyond the English system.

The relationship between national context and science or Archer-style engineering capital can be explored within this thesis dataset. Whilst sample sizes differed for England and Scotland in this dataset limiting the ability to draw deeper conclusions the analysis might be considered as a suggestive examination of national context and capitals for science and engineering. Two independent samples t-tests were used to explore how scores for science capital and Archer-style engineering capital differed by national context. The first t-test identified a significant difference in science capital by nation ($t(919) = 2.313$, $p=0.021$, $d=.258$), with science capital mean scores in England ($M=41.69$, $SD=13.98$) higher than in Scotland ($M=38.08$, $SD=14.33$). The second t-test revealed no significant difference in Archer-style engineering scores by nation ($t(919) = -0.218$, $p=0.827$) with national means not significantly differing for England ($M=34.10$, $SD=13.44$) and Scotland ($M=34.43$, $SD=14.12$) (see Appendix E for statistical outputs).

Whilst it is important to maintain that the sampling of Scotland was limited, so deeper conclusions should not be drawn from this data, these findings may be considered as suggestive of the relationship between nation context and scores for science and engineering capitals. These analyses suggest that science and Archer-style engineering capital differ in their relationship to national context. In particular, the significant difference in science capital scores between the English and Scottish context are insightful given that previous study of science capital has been based in the English context. The difference identified bears implications for the adoption of science capital outside of England – a presumption that the distribution of science capital in Scotland is the same as in England would overestimate the capitals held by young Scottish people. This speaks further to the scope of science capital and its potential unrecognised limitations in contexts other than England. However, this must be further studied with more representative samples.

The lack of significant difference for Archer-style engineering capital, despite the significant findings for science capital, suggests further that the two are not aligned. This demands further investigation, particularly given the greater presence of engineering within the Scottish curricula. A more representative sample, perhaps with matched samples in England and Scotland would be more capable of examining this directly. Such an investigation would support the refinement of capital models to examine inequity within the UK.

Discussion and Conclusions on Hypothesis One

Hypothesis One: Scores measured on the science capital instrument are predicted to significantly differ from scores on a similarly structured instrument of engineering capital.

The comparative measurement of capitals for science and engineering within this thesis confirms the prediction of hypothesis one that science and Archer-style engineering capital scores differ. This validates the position that science capital is not reflective of capital for engineering and that the adoption of science capital to understand engineering inequity will not be as valid as its adoption to understanding inequities in science.

Analysis of the distribution of science and engineering capital amongst UK secondary school learners shows that engineering capital is less prevalent than science capital within this population and that use of the science capital model to investigate engineering would miscalculate the level of supportive resources present for engineering. Analysis of gender differences – a key element of engineering inequity – demonstrates that the science capital model is not sensitive to differences in resources between boys and girls in secondary education, further questioning the fidelity of science capital in examining engineering inequity. Whilst sample sizes are limited, these analyses also suggest that the relationship between academic ability for science and capitals for science and engineering differ questioning how well the science capital model can be used to understand those still in education or the inequities of educational pathway decision making. The same is true for the relationship between science and engineering capitals and national context, with questions as to the relationship between these measures of inequities in secondary learners in differing national settings.

Overall, these findings posit that science capital is a poorer measure of engineering inequity compared to an engineering-specific model of capital. The differences identified in the measurement of capitals for engineering or science demonstrate a difference in capitals for these subjects that is not accounted for within a model of science capital. Given the complexity of inequity it is crucial to adopt as accurate a model as possible in framing and measuring these issues. The identification of differences between science capital and an engineering capital model supports the rejection of science capital and the adoption of a novel model of engineering proposed in this thesis to investigate engineering inequity in the UK context.

Results and Discussion – Hypothesis Two

<u>*Hypothesis Two*</u>**:** *A model of engineering capital is predicted to hold greater power in explaining and predicting patterns of inequity in engineering education and career aspiration compared to models of science or arts-based Bourdieuian capital.*

Whilst the analyses of hypothesis one confirm that science capital and Archer-style engineering capital differ, they cannot conclusively reject the adoption of science capital to investigate engineering inequities. It is possible that differences between these models, whilst observable, produce little impact to the application of these models in investigations of engineering educational or career inequities. As a result, before the adoption of science capital can be rejected within this thesis it is necessary to apply these models to engineering inequities to confirm their utility. Hypothesis two is thereby concerned with confirming an engineering-specific capital model is more effective in understanding inequity.

To explore this, binary logistic regression analyses were adopted to compare the accuracy with which models of science capital, Archer-style engineering capital and arts-based, general cultural capital can understand the variance, or predict, educational and career inequities amongst secondary school-aged learners. The greater the accuracy of each model, the better its fit to engineering inequities.

<u>Engineering Educational Aspiration</u>

Access and participation with engineering educational trajectories is recognised as deeply inequitable with limited and homogenous participation observed within the very first opportunities for young learners to shape their educational experience. Educational aspirations were adopted within the science capital literature as an indicator of the alignment of young learners to a future in science (Archer et al., 2015). As a result, any model which proposes to investigate engineering inequity must be responsive to educational inequities. Three binary logistic regression analyses were completed examining the accuracy of engineering educational aspiration predictions by models of: Archer-style engineering capital, science capital, and Bourdieuian general cultural capital.

The first binary logistic regression was performed to determine the effects of Archer-style engineering capital on the likelihood of aspiring to engineering education. The logistic regression model was statistically significant ($x^2(1) = 219.683$, $p<0.001$). The model explained 32.3% of the variance (Nagelkerke R^2) in engineering education aspiration with an overall predictive accuracy of 80.4%. A deeper examination of this accuracy reveals that Archer-style engineering capital has a sensitivity (accuracy of true positives or, accuracy identifying those wishing to study engineering) of 43%, and a specificity (accuracy of true negatives or, accuracy identifying those who do not wish to study engineering) of 93.3% (see Appendix E for statistical outputs).

The second binary logistic regression was performed to determine the effects of science capital on likelihood of aspiring to engineering education. The logistic regression model was also statistically significant ($x^2(1) = 9.938$, $p=0.002$). The model explained only 1.6% of the variance (Nagelkerke R^2) in engineering education aspiration with an overall predictive accuracy of 74.3%. A deeper examination of this accuracy reveals that science capital has a sensitivity (accuracy of true positives) of 0.0%, and a specificity (accuracy of true negatives) of 100.0%. This deeper examination shows that the model of science capital is only accurate at identifying those who do not aspire to engineering education and detects 0% of those that do aspire to study engineering. This clearly demonstrates the lack of value in science capital for purposes of understanding engineering inequity as it holds no sensitivity to identify those who aspire to study engineering and no ability to discern patterns in this inequity (see Appendix E for statistical outputs).

The third binary logistic regression was performed to determine the effects of general cultural capital on likelihood of aspiring to engineering education. The logistic regression model was not statistically significant ($x^2(1) = 0.076$, $p=783$). The model explained 0.0% of the variance (Nagelkerke R^2) in engineering educational aspiration with an overall accuracy of 74.3%. A deeper examination of this accuracy reveals that general cultural capital has a sensitivity (accuracy of true positives) of 0.0%, and a specificity (accuracy of true negatives) of 100.0%. As with science capital, the general cultural capital model could not effectively predict who did aspire to future engineering education (see Appendix E for statistical outputs). These results are outlined on Table 4.06 below.

Table 4.06: Binary logistic regression analyses results for predictions of engineering educational aspiration by models of Archer-style engineering, science and general cultural capital.

Model	**Significant Chi-Square**	**Loglikeli.**	**Nagelkerke R^2**	**Accuracy**	**Sensitivity (true pos.)**	**Specificity (true neg.)**
Archer-Style Engineering Capital	Yes (p<0.001)	791.399	32.3%	80.4%	43.0%	93.3%
Science Capital	Yes (p<0.001)	1001.144	1.6%	74.3%	0.0%	100.0%
General Cultural Capital	No (p=0.783)	1011.006	0.0%	74.3%	0.0%	100.0%

A comparison of these results reveal that the three models are not equal in their ability to explain the variance in engineering educational aspiration. The Archer-style engineering capital model vastly outperforms the models of science capital or general cultural capital, explaining 32.3% of the variance in engineering educational inequity compared to only 1.6% by science capital and 0.0% by general cultural capital. Overall accuracy of prediction is also greater for Archer-style engineering capital (80.4%) compared to science capital (74.3%) and general cultural capital (74.3%). At first, this would appear to minimise the advantage of an engineering-specific model of capital, only offering a 6.1% improvement over science capital, however a deeper analysis of prediction accuracy validates the greater value of the engineering capital model.

Overall accuracy can be broken down into sensitivity and specificity, otherwise known as true positive and true negative accuracies. The sensitivity of these models - their ability to detect those who aspire to engineering education – is much greater for Archer-style engineering capital (43.0%) than for science capital (0.0%) or general cultural capital (0.0%). In other words, the models of science capital and general cultural capital could not accurately identify a single participant who wished to study engineering. This is markedly false, as 24.7% of participants indicated that they aspired to some form of engineering education. Whilst Archer-style engineering capital only had a sensitivity of 43.3%, which it might be argued leaves room for improvement, it still represents a clear improvement on science capital. Predicting a complex state such as desire for future engineering education, without directly asking about it, is difficult and the Archer-style engineering capital model does this reasonably well.

An uncritical analysis of the accuracy of these models in predicting engineering educational aspiration would at first suggest that they are vaguely similar, with Archer-style engineering capital only 6.1% more accurate. However, a richer analysis reveals that science capital and general cultural capital are not at all predictive, and only appear to be by assuming every individual does not aspire to engineering education. This only gives the appearance of validity as engineering educational aspiration is uncommon within this population, however the lack of discernment between those who do and do not aspire to engineering study means that these models are of no value for understanding and addressing engineering inequity. These findings further align to the position adopted within this thesis that engineering and science share a complex relationship: despite the interconnection of these domains a science capital lens is unhelpful for understanding engineering inequity.

These findings also demonstrate that the arts-based general cultural capital model is a poor fit to engineering educational aspirations, despite the theoretical link between this arts-based view and the creative design processes of engineering. Given the popularity of the Bourdieuian cultural capital model and science capital as perspectives on inequity, the lack of statistical significance and predictive power in relation to engineering inequity is worrying. This further demonstrates the need for a model of inequity specifically focused on engineering in the UK context.

Engineering Career Aspiration

Career aspirations, as with educational aspirations, were also a benchmark for inequity used to examine science capital, representing the inequitable future trajectories of young people towards science (Archer et al., 2015). As with educational aspiration three binary logistic regression analyses were completed to examine the accuracy of engineering career aspiration prediction by the models of Archer-style engineering capital, science capital and Bourdieuian general cultural capital.

The first binary logistic regression was performed to determine the effects of Archer-style engineering capital on the likelihood of aspiring to a future engineering career. The logistic regression model was statistically significant ($x^2(1) = 296.034$, $p<0.001$). The model explained 38.8% of variance (Nagelkerke R^2) in engineering career aspiration with an overall accuracy of 75.8%. A deeper examination of this accuracy reveals that Archer-style engineering capital has a sensitivity (accuracy of true positives or, accuracy identifying those wishing to work in engineering) of 54.4% and a specificity (accuracy of true negatives or, accuracy identifying those who do not wish to study engineering) of 87.5% (see Appendix E for statistical outputs).

The second binary logistic regression was performed to determine the effects of science capital on the likelihood of aspiring to a future engineering career. The logistic regression model was statistically significant ($x^2(1) = 8.990$, $p=0.003$). The model explained 1.4% of variance (Nagelkerke R^2) in engineering career aspiration with an overall accuracy of 64.9%. A deeper examination of this accuracy reveals that science capital has a sensitivity (accuracy of true positives) of 0.9% and a specificity (accuracy of true negatives) of 100.0%. As with the use of science capital with engineering educational aspiration the model of science capital does not accurately predict those who wish work in engineering roles and is thereby incompatible with such considerations of engineering inequity (see Appendix E for statistical outputs).

The third binary logistic regression was performed to determine the effects of general cultural capital on the likelihood of aspiring to a future engineering career. The logistic regression model was not statistically significant ($x^2(1) = 1.219$, $p=0.270$). The model explained only 0.2% of variance (Nagelkerke R^2) in engineering career aspiration with an overall accuracy of 75.8%. A deeper examination of this accuracy reveals that general cultural capital has a sensitivity (accuracy of true positives) of 0.0% and a specificity (accuracy of true negatives) of 100.0%. The statistically insignificant predictive power of Bourdieuian cultural capital highlights its incompatibility in predicting engineering career aspiration. As a result, it is of questionable use to support efforts to address engineering inequity (see Appendix E for statistical outputs). These results are outlined on Table 4.07.

Table 4.07: Binary logistic regression analyses results for predictions of engineering career aspiration by models of Archer-style engineering, science and general cultural capital.

Model	**Significant Chi-Square**	**Loglikeli.**	**Nagelkerke R^2**	**Accuracy**	**Sensitivity (true pos)**	**Specificity (true neg)**
Archer-style Engineering Capital	Yes ($p<0.001$)	863.645	38.8%	75.8%	54.4%	87.5%
Science Capital	Yes ($p=0.003$)	1150.689	1.4%	64.9%	0.9%	100.0%
General Cultural Capital	No ($p=0.270$)	1158.459	0.2%	64.6%	0.0%	100.0%

As with engineering educational aspiration, comparison of these regression analyses allows the utility of the three models to be determined in relation to their ability to predict engineering career aspiration. Given that career aspiration is a key indicator of engineering inequity, representing the trajectory of individuals towards engineering practice as adults and the related entrenched patterns of inequity, the ability of models to accurately predict engineering career aspiration is a vital prerequisite for a model of engineering inequity. Whilst employment will still be a number of years away for most secondary school-aged participants a desire to work in an engineering role can be used to indicate alignment for an engineering future and is a relevant consideration given the established patterns of inequity in engineering careers. The greater the variance of engineering career aspiration data explained by a model, the greater its ability to understand the phenomena.

Comparisons reveal that only Archer-style engineering capital and science capital are significantly predictive of engineering career aspiration, with Archer-style engineering capital predictive to a $p<0.001$ level and science capital to a $p=0.003$ level. Bourdieuian cultural capital, on the other hand, is not found to be significantly predictive with a p-value of 0.270. This is noteworthy considering that general cultural capital was predictive of educational aspiration for engineering but is not found to be predictive of career aspiration. This suggests that educational and career aspirations are not the same (which is confirmed by a frequency analysis revealing that whilst 24.7% of this sample aspire to engineering education 34.3% aspire to an engineering-related career). The significant predictive power of Archer-style engineering capital and science capital would appear to validate their use to consider engineering career aspirations, however the two models are not equal in their utility. The Archer-style engineering capital model is found to explain more variance in career aspirations (38.8%) than science capital (1.4%). Archer-style engineering capital can vastly outperform in terms of sensitivity, the identification of true positives/those who aspire to engineering careers with a 54.4% accuracy compared to 0.9% by science capital. This means that whilst Archer-style engineering capital can identify more than half of those who wish to work in engineering roles, science capital can only identify less than one in one hundred. This represents a vastly different capacity to relate to engineering inequity and demonstrates the vastly differing levels of utility of these models. Whereas a 54.4% accuracy is clearly limited and has room for improvements the Archer-style engineering capital model is much more useful than the 0.9% accuracy of science capital. This is further supported by comparing the specificity of these models – their ability to identify true negatives/those who do not want to work in engineering careers. Here Archer-style engineering capital is outperformed, with a specificity of 87.5% compared to 100% by science capital. However, this is not a validation of science capital as this 100% accuracy is only established through predicting all participants do not wish to engage with engineering careers – which is not the case as 34.3% reportedly do. It can thereby be argued that the science capital model is not a predictive model of engineering career aspiration at all. A model might only be considered predictive if it attempts to delineate and identify distinct groups.

In the case of science capital, the model only appears accurate for engineering career aspiration to a degree because this aspiration is relatively uncommon and the science capital model predicts that no one will want to enter such careers. This offers zero utility in trying to understand, predict or measure engineering career aspirations in relation to engineering inequity as its ecological validity is nil. This further highlights the value of an engineering-specific model of capital and demonstrates the relative weakness of science capital to explain the variance in career aspirations for engineering.

Discussion and Conclusions on Hypothesis Two

Hypothesis Two**:** *A model of engineering capital is predicted to hold greater power in explaining and predicting patterns of inequity in engineering education and career aspiration compared to models of science or arts-based Bourdieuian capital.*

Originating in a rationale that more specific models of capital are likely more accurate in relation to their specific domain, hypothesis two predicted that an engineering capital model would outperform models of science or general cultural capital in understanding engineering inequity. Analyses examining the ability of these models to explain and predict inequities in engineering validate this hypothesis and demonstrate the need for an engineering capital model.

The engineering capital model is found to vastly outperform the science capital model. This contrasts with past claims for science capital as a potential STEM capital model by researchers involved in the ongoing science capital literature:

"*We suggest that the reported associations between science capital and aspirations and attitudes to engineering, maths, and technology indicate that the concept can, to a certain extent, be interpreted as representing not just science capital, but a wider, broader 'STEM capital'. In other words, based on the correlations reported in this article (with significant and meaningful relationships found beyond science attitudes, that is, also between science capital and TEM attitudes), science capital may share enough similarities to 'STEM capital' to be used as a reasonable proxy.*" (Moote et al., 2020, p1241).

Bourdieuian general cultural capital is similarly found to lack a specificity and accuracy in understanding engineering inequity, despite the theoretical justification that this arts-based model may carry some relevance to engineering as a creative process with artistic parallels (Cropley, 2016; Silva, 2008). The empirical findings demonstrate a weak power or no significant relationship between this model of general cultural capital and engineering inequity which itself speaks to the need for specificity in the focus of a capital-based perspective on participation and representation. The theoretical justification that a capital model based on artistic taste could represent engineering carries the same biases of generalisation and abstraction that face the relevance of the science capital model.

Whilst established as a tremendously helpful perspective and model of science inequity, these findings show that the science capital model is a poor fit to the specific patterns of inequity found in the engineering domain. Science capital could not accurately distinguish secondary school students who did or did not aspire to engineering education or careers, and so cannot be seen to reflect patterns of participation or representation in engineering inequity. The lack of fit between science capital and engineering also questions the degree to which interventions developed from the science capital perspective such as the Science Capital Teaching Approach might apply to engineering. In light of these findings the use of the science capital model to understand engineering inequity can be seen to endanger the accuracy and success of efforts to understand and address engineering inequities. The limited progress in addressing engineering inequities in the UK, compared to progress for science, may be in part due to such presumed relevance of science interventions for engineering inequities.

The greater accuracy and predictive power of the Archer-style engineering capital model demonstrates the usefulness of a domain specific model of capital in inequity. Whilst only able to correctly identify 43.0% of those who wish to study engineering and 54.4% of those who wish to work in engineering roles this model might be considered a proof of concept for a more sophisticated and nuanced model of capitals for engineering. The Archer-style engineering capital model used in these analyses was formed through the translation of the science capital instrument and so only considered the forms of capital identified as relevant to the science domain. The development of a new model of engineering capital which focuses on those capitals that are instead most relevant to the engineering domain will likely improve the power of this model to aid understanding, measurement, and predictions of engineering inequity.

Chapter Discussion

The empirical findings outlined in this chapter not only validate the predictions of hypotheses one and two but also provide a sophisticated insight into the relationship between the domains of science and engineering and the value of science capital as a lens for engineering inequity. These findings include many novel insights.

Despite the popularity of its theoretical perspective few empirical studies of science capital have been conducted within research literature. It may be expected that the distribution of science capital within the UK will change over time, naturally or through the impact of interventions such as the Science Capital

Teaching Approach, which necessitates a need to revisit this perspective empirically to ensure the continuing relevance of established understanding. The findings of this thesis offer a more recent empirical perspective on science capital than past studies (Archer et al., 2015; Moote et al., 2021). Analyses used to test hypothesis one reiterated past findings such as the inequitable distribution of science capital within secondary school-aged participants, but also dissented from established findings such as the gendered inequities in science capital which was not established in this thesis sample (Archer et al., 2015). These examinations also considered science capital in new ways such as in the comparison of science capital scores in differing national contexts (England and Scotland) or in relation to engineering aspirations. Little examination has also directly investigated the relationship between science capital and other STEM domains. The findings of this thesis disagree with past, more simplistic empirical findings that suggest science capital applies to STEM inequities and instead puts forwards the case for domain-specific models of capital. This would suggest that the specific patterns of nuance within inequities cannot be generalised based on surface level similarities or abstractions between domains. These findings do question the use of science capital in engineering or in a generalised 'STEM capital' manner which is suggested in wider literature (EngineeringUK, 2020; Greater Manchester Combined Authority, 2019; Institution of Engineering and Technology, 2022). Given the continuing popularity of science capital these findings offer a novel insight into the continuing relevance and scope of this tool and the evolving patterns of science inequity found in the UK context.

The most significant novel insight from this empirical investigation is the validation of an engineering-specific capital perspective for understanding and addressing engineering inequities. Whilst the accuracy of the Archer-style engineering capital instrument in predicting patterns of engineering inequity was not quite high enough to warrant deployment in real settings its strong performance over the science capital model demonstrates that an engineering-specific approach, if iterated and improved upon, possesses great value. The empirical measurement of Archer-style engineering capital has also supported a more sophisticated understanding of engineering inequity in the UK – demonstrating patterns of aspiration for engineering education and careers in a fashion infrequently examined in the UK context. The value of these insights further motivates the development of an engineering-specific model of capital.

Conclusions

In this chapter the science capital model was empirically investigated to determine its relevance to inequities within the engineering domain. In line with the theoretical critique outlined in previous chapters it was determined that science capital is a weak model to adopt for the purpose of developing greater understanding of engineering inequities in the United Kingdom. A simplistic model of engineering capital was developed through translation of the science capital instrument to support the value of an engineering-specific approach to engineering inequity. Two hypotheses were tested to establish this finding. The first determined that capitals for engineering and science differed from one another and in relation to characteristics central to engineering inequity in the UK. The second hypothesis showed that science capital could not be used to predict patterns of engineering inequity questioning the validity of its perspective for this application. These analyses do not support the use of science capital to investigate and understand patterns of engineering inequity in the UK. However, these findings do highlight the potential value in an engineering-specific model of capital. The effective domain-specific application of the Bourdieuian framework to science inequity demonstrated by Archer and colleagues supports the adoption of the Bourdieuian perspective to examine engineering inequity in later chapters of this thesis. Whilst not applicable to the engineering domain Archer et al.’s science capital model can also be drawn on as an exemplar of Bourdieuian-based model and instrument development in later chapters. The effective domain-specific application of Bourdieuian capital for science inequities does demonstrate the potential use of this conceptual framework to better understand inequities in the engineering domain. In the following chapters a model of engineering capital will be developed and tested. In Chapter Five an instrument development process will be adopted and theoretical model of engineering capital established drawing on the insights offered by the Archer-style engineering capital model.

CHAPTER FIVE: FORMING A THEORETICAL MODEL OF ENGINEERING CAPITAL

Introduction

In previous chapters, it was theoretically and empirically established that science capital offers a poor fit to engineering inequity. Despite this, the Bourdieuian capital lens was suggested to apply to the issue of engineering inequity if applied in an engineering-specific manner. This endorses the development of an engineering capital model to support the objective of this thesis and advance understanding of engineering inequity. In the following chapter this development begins drawing on the approach undertaken by Archer et al. (2015) in the formation of their successful science capital model. Recognising that little literature has considered the science capital approach as a replicable methodology Archer et al.'s approach is first critically considered in relation to instrument development literature to validate its adoption. Having concluded that this approach is valid, the first two stages of this four-stage process will be completed to create a conceptual framework and theoretical model of engineering capital. By aggregating and reinterpreting past literature through a Bourdieuian lens a more sophisticated theoretical model of engineering inequity is outlined and offered for practical application.

Forming a Model of Engineering Capital

The previous chapters of this thesis establish a poor theoretical and empirical fit between the science capital model and patterns of engineering inequity amongst young UK learners. Despite its validity as a science inequity perspective, the science capital model was determined to possess a limited utility within the engineering domain. A translated science capital instrument that instead examined capitals within the engineering domain demonstrated a greater usefulness in understanding patterns of educational and career aspiration for engineering amongst young learners. This engineering-specific approach offered greater nuance in understanding the distribution of supportive resources amongst this population, and thereby provided a proof-of-concept for the use of this capital perspective within the engineering domain. These findings demonstrate the value of adopting the Bourdieuian framework in a contemporary, domain-specific fashion to support examinations of inequity and the utility of Archer et al.'s approach to Bourdieuian-based model and instrument development. However, it must be noted that the translated 'Archer-style engineering capital' model developed in Chapter Four, as a product derived from the science capital development process, only examines the forms of capital most influential for the science domain.

As established in the Chapter One and Chapter Three, this thesis adopts the position that engineering and science are significantly distinct. Therefore, we must consider whether the forms of capital most influential for engineering differ from those for science and so included in the science capital and 'Archer-style engineering capital' instruments. The logical next step is to develop an engineering-specific model of capital with an engineering-specific focus, rather than translating the product of a science-specific approach.

Although the *product* of Archer and colleagues' work is argued to not fit closely with engineering, the *process* through which it was developed may be suitable for adoption as a domain-specific capital model development procedure. The utility of the science capital model to the science domain demonstrates the potential for this procedure to produce a significant and useful model of domain-specific capital. Little or no research has seemingly considered the potential for the science capital formative literature to act as a guide to capital instrument development. The science capital literature does not explicitly refer to instrument development literature, instead focusing on the Bourdieuian underpinning of the model. It is therefore necessary to critique this process to determine its rigour and suitability for use in developing an engineering capital model.

An examination of instrument development literature can provide a perspective on Archer et al.'s capital instrument development procedure. Instrument development processes are often framed as linear progressions involving multiple stages that are sequentially completed to form a robust instrument. Benson and Clark (1982) offer a well-cited four stage process of instrument development involving planning, construction, evaluation and validation. These stages are outlined in Table 5.01 below.

Table 5.01: Benson and Clark's (1982) four stage instrument development process.

Development Process Stage	**Stage Tasks/Objectives**
Planning	Instrument developers set their purpose and domain of focus, conduct literature reviews around the instrument topic, develop objectives and select the format for the instrument questions.
Construction	Developers generate items, refine these through content validation, and revise items.
Evaluation	Developers pilot test items, check reliability and internal consistency of scales, revise items and collect data.
Validation	Multiple applications of the instrument are completed to confirm its validity and success.

The Benson and Clark (1982) procedure offers a useful roadmap of the process through which an instrument can not only be formed but refined to maximise the validity and reliability of its measurement. Alternative procedures, such as the 'MEASURE' process proposed by Kalkbrenner (2021) follow a similar overarching process. The MEASURE process (Make the purpose clear, Establish empirical framework, Articulate theoretical blueprint, Synthesise content and scale development, Use expert reviewers, Recruit participants, and Evaluate validity and reliability) overlaps with the stages of Benson and Clark's process, supporting the validity of this approach.

Archer et al.'s (2015) methodology for forming the science capital model can be framed in similar terms. The science capital development methodology, as with Benson and Clark's (1982) instrument development methodology, also breaks down into four stages:

- The development of a conceptual framework,
- The formation of a theoretical model of capital,
- The empirical examination and formation of the instrument, and
- The applications of the resulting capital model to inequity.

This is visualised in Table 5.02 below.

Table 5.02: Overlaid stages of instrument development in Benson and Clark (1982), Kalkbrenner (2021) and Archer et al.'s (2015) science capital methodology.

Stages of Instrument Development in Three Approaches		
Archer et al.'s (2015) Science Capital Development Methodology	**Benson and Clark (1982) Instrument Development Methodology**	**Kalkbrenner (2021) 'MEASURE' Instrument Development Methodology**
The development of a conceptual framework	Planning	Make the purpose clear
		Establish empirical framework
The formation of a theoretical model of science capital		Articulate theoretical blueprint
	Construction	Synthesise content and scale development
		Use expert reviewers
The empirical examination and formation of the instrument	Quantitative evaluation	Recruit participants

Applications of the resulting science capital model to science inequity.	Validation	Evaluate validity and reliability

Each of Archer et al.'s four stages can be explored in greater detail to determine the efficacy and potential application of this instrument development process to form a model of engineering capital. The linearity of this process is key as earlier stages will influence the shaping and contents of subsequent stages leading to the final product of engineering capital. In this manner each stage is vitally important and must be established as compatible with the objective of forming a capital model for engineering. This analysis will determine the adoption of Archer et al.'s approach to forming a domain-specific capital model in this thesis.

The development of a conceptual framework

The first stage of Archer et al.'s instrument development procedure involves the formation of a conceptual framework: a series of interconnected concepts that set out the foundation of its relationship with the subject matter (Leshem & Trafford, 2007). This stage relates to what Benson and Clark (1982) would refer to as the planning stage and what Kalkbrenner (2021) would call the 'make the purpose clear' and 'establish empirical framework' stages of instrument development. The conceptual framework is, as Bordage (2009, p318) describes, a "[way] of thinking about a problem or study, or [way] of representing how complex things work". Within the context of the instrument development process, this acts as a bearing for the later stages and carries through to the design, implementation and examination of the newly created model (Jabreen, 2009; McGaghie et al., 2001). A clearly articulated conceptual framework is a key step in developing a focused and purposeful instrument.

The conceptual framework within Archer and colleagues' application of their procedure focuses on the concepts of 'science', 'equity' and 'Bourdieuian capital' but notably not all three concepts are framed in explicit detail. The concept of 'science' is poorly articulated in the formative literature of science capital, leading to uncertainty as to its scope and necessitating further examinations such as in Chapters Two and Four of this thesis (see Archer et al., 2015). This demonstrates the importance of clarity in conceptual framing and the resulting impact on later stages of the process as unclear conceptual framings continue to impact the application and utility of the science capital model. The conceptual framing of equity (focusing on post-16 science aspirations) and Bourdieuian capital (that capitals for science may offer a valid perspective on inequity) in Archer et al.'s (2015) application of the development process are more clearly articulated.

The inclusion of a distinct conceptual framework stage within the instrument development process ensures that the 'ways of thinking about a problem' are clearly focused to the purpose of instrument development. A conceptual framework is a necessity for effective model or instrument development and in this way Archer et al.'s approach can been judged as following good practice (Antonenko, 2015; Benson & Clark, 1982). This first stage collates and manages the abstractions of the instrument development process and focuses these to the purpose of this procedure (Weaver-Hart, 1988). By framing both the focus of the instrument (science inequity) and the lens used to examine this focus (Bourdieuian capital) the conceptual framework stage of the instrument development process addresses what Punch (2000) refers to as the 'what' and 'how' questions of research, supporting the clarity of the development process.

The first stage of Archer et al.'s capital instrument development process must be acknowledged as compatible with further instrument development procedures (Benson and Clark, 1982; Kalkbrenner, 2021). This stage provides a rigorous and clear foundation to the process of capital model development that is compatible with the need recognised in this thesis to develop detailed, engineering-specific examinations of inequity to address a scarcity of understanding. The development of a clear conceptual framework is arguably more necessary in the development of an engineering capital model than a science capital model due to the ambiguity of 'engineering' and the inconsistency with which is it aligned or distinguished from 'science' or 'STEM' in past literature and wider culture (Lyons, 2018; Peters-Burton, 2014). The presence of science within national curricula contributes to a shared societal notion of what 'science' is, which is not the case for engineering as demonstrated by examinations of public understanding outlined in Chapter One (Marshall et al., 2007). A clear conceptual framework is therefore crucial in approaching engineering inequity to ensure a clarity of what engineering is and how it is examined within an instrument. This first stage of Archer and colleagues' capital model development process is therefore appropriate for use in developing an engineering capital model, though the contents of this conceptual framework must focus solely on engineering.

The formation of a theoretical model of capital

The second stage of Archer et al.'s domain specific capital instrument development process involves the literature-led formation of a theoretical model drawing on the conceptual framework established in the first stage. Benson and Clark (1982) might still consider this a planning stage, whilst Kalkbrenner (2021) would frame this as ‘articulating the theoretical blueprint’. This literature-led approach involves the examination of domain-specific inequity through the Bourdieuian lens. Archer et al.’s (2015) adoption identified seven ‘subcomponents’ of science capital from past literature. The utilisation of wider literature in the instrument development process supports the content validity of its resulting product and entrenches this novel development within the context of current understanding (Sireci, 1998). The clarity of the earlier conceptual framework provides clear guidelines for the inclusion of elements into the theoretical model that are consistent with the intention of the instrument development process. The theoretical model produced through this process can be understood as a synthesising aggregate of wider findings within a singular model.

Though beneficial to the content validity of the instrument development process, this aggregating structure to model development also introduces distinct risks. Complex systems theory acknowledges that an interconnected structure of elements can result chaotically to change in any one element through a cascading impact on connected elements. Therefore, whilst an aggregating approach to theoretical model development is more complex and perhaps reflective of real-world conditions, such approaches may produce models and instruments that are vulnerable to change over time (Koopmans, 2020; Lemke & Sabelli, 2008). This is demonstrated for the science capital model in Chapter Four of this thesis where questions are raised as to the continuing validity of patterns of science capital results identified almost a decade ago. However, this itself may be framed as an ecologically valid approach to model and instrument development given the Bourdieuian lens is centred on the socially stratified nature of culture – and so is inherently concerned with elements that have the potential to change over time. As a result, despite its vulnerability to change over time, Archer et al.’s approach to theoretical modelling in the instrument development process is capable of producing ecologically valid products if ongoing validation is maintained.

This stage of Archer et al.’s instrument development approach is compatible with the objectives of this thesis in developing a model and measure of engineering inequity. The synthesis of wider literature under a common way of thinking, in this case Bourdieuian capital (even if this literature is not itself concerned with capital), offers value to the study of engineering inequity and contributes to a cross-cutting enrichment of contemporary understanding. Whilst Archer and colleagues’ use of this process benefitted from the rich body of science equity literature, using this approach for engineering may be challenged by the comparatively lesser available literature on UK engineering inequity. This does not discount the use of this approach to instrument development, but it must be acknowledged that a lesser volume of raw materials is available. However, regardless, this approach will contribute to the sum of understanding around engineering and it may be that other domain specific utilisations of Bourdieuian capital could be critically considered as potentially relevant to engineering. On balance, the complexity of engineering inequity dictates the need for a multi-faceted approach to theoretically modelling engineering capital such as that offered by Archer and colleagues' instrument development process supporting the adoption of this approach.

The empirical examination and formation of the instrument

Where stages one and two of Archer et al.'s domain-specific capital instrument development process are concerned with theoretical aspects, stage three sees the shift to empirical development. This stage sees the creation of an empirical questionnaire drawing on the theoretical model, data collection from relevant audiences and data processing to identify the most effective empirical instrument possible. Benson and Clark (1982) would view this process as 'quantitative evaluation', whilst Kalkbrenner (2021) would identify this as 'synthesise content and scale development' and 'recruit participants'. In Archer et al.'s own use of this instrument development process a questionnaire was formed drawing on existing, validated, non-Bourdieuian instruments such as the Public Attitudes to Science (IPSOS Mori, 2011) and ASPIRES data collection surveys (Archer et al., 2013) as well as through novel items created for the questionnaire. This adoption and synthesis of existing items both connects the questionnaire to wider literature and supports the potential criterion validity of the resulting data collection tool (McDonald, 2005). This questionnaire was utilised to collect data from secondary school-aged participants. Following data collection, responses were analysed using Principal Components Analysis, Logistic Regression Analysis and Cronbach's Alpha analyses to refine this questionnaire to form a smaller instrument to measure capitals for science.

This approach to instrument development is robust, utilising a statistical method of formation that limits subjective judgement and relies on objective measurements to determine the structure of the resulting instrument. Such a data-led approach is valid and ensures that influences not included in the theoretical model, but active within real world settings, can influence the collected data and therefore the resulting instrument. This process would also be suitable for the development of a model of engineering capital. As with the lesser volume of literature there are also fewer existing instruments that measure engineering inequity from which to draw from in comparison with the domain of science. However, as demonstrated by the 'Archer-style engineering capital' model in Chapter Four, it is possible to adapt questionnaire items from non-engineering contexts to produce a viable instrument. Some adjustments to this data collection strategy would be necessary, such as the expansion of data collection beyond Archer and colleagues'

England-only sample to also include wider UK contexts and thereby support the robustness of the engineering capital model produced through this process, yet the overarching methodological approach is valid.

Applications of the resulting capital model to inequity

The final stage of Archer et al.'s instrument development process involves the application of the instrument to test its reliability, validity and utility for its designed purpose of understanding domain-specific inequity. Benson and Clark (1982) would view this process as the validation stage whilst Kalkbrenner (2021) would frame this as 'evaluation of validity and reliability'. Benson and Clark (1982) view such testing as something that must occur beyond the scope of initial instrument development through continued application: "The validation of a newly developed instrument is almost never accomplished through one study or by one researcher. Instead, it requires numerous research efforts and, for this reason, must be considered an ongoing process." (Benson and Clark, 1982, p798). This sentiment is echoed by Streiner and Kottner (2014) who note that no one study, in this case the formative process of developing an instrument, can 'prove' the reliability of an instrument, as this only comes from repeated use and testing. Repetitive applications are necessary to confirm the value of even a robustly constructed tool given the complexity of practical settings.

Within Archer et al.'s instrument development process, validation is developed throughout the procedure with face validity developed in the clearly structured conceptual framework, content validity developed through aggregation of past literature in the theoretical model, and reliability and criterion validity developed in the empirical examination of engineering capital in stage three. Archer et al.'s continued use of the science capital instrument in subsequent publications aligns to the view of Streiner and Kottner that validation is an ongoing process (Moote et al., 2020; Moote et al., 2021; Streiner and Kottner, 2014). In particular, DeWitt et al.'s (2016) examination tested the validity of the resulting domain specific capital model in relation to a sample of underrepresented individuals testing the scope of the instrument.

This final stage of the domain-specific capital instrument development process is also appropriate for use in this thesis to examine engineering inequity. A final stage of ongoing testing is appropriate and reflective of the objective of this thesis in developing greater understanding of engineering inequity in the UK context. An engineering capital model and instrument, as a tool of understanding and measurement, can be seen as only holding value whilst holding utility to its designed purpose. An ongoing agenda of application and testing is not only methodologically necessary but also aligned to the need to expand on understanding and interventions with engineering inequity in the UK. It must be acknowledged, however, that the bounds of this thesis project may limit the degree to which validation could take place over time but a foundation of application can be established and, if the model is effective, further testing encouraged.

Adoption of Archer et al.'s (2015) Instrument Development Approach

The four-stage instrument development process utilised by Archer and colleagues to create the domain-specific model and instrument of science capital aligns with wider literature on instrument development. The process is robust utilising validity and reliability testing to confirm the theoretical and empirical significance of its contents. An instrument developed through this process is not only theoretically grounded in wider literature but informed by empirical data collected from within practical settings. Although not introduced in science capital literature as a methodology for domain-specific capital model development, this critique suggests that the process is not only relevant to the science domain but can inform future models of domain-specific capital. Whilst Chapters Two and Four of this thesis demonstrate that the direct adoption of science capital is inappropriate for examining the engineering domain, this analysis suggests the work of Archer and colleagues can be indirectly adopted as a methodology to create a model of engineering capital. The instrument development process is compatible with the needs of this thesis in developing an engineering-specific, theoretically informed, empirically guided structure of engineering inequity in the UK to bolster understanding and aid intervention.

In the remainder of this chapter the first two stages of this instrument development process, representing the theoretical stages of the procedure, will be completed. First, a conceptual framework of engineering capital will be outlined. Next, a theoretical model will be developed drawing on wider literature interpreted through the lens of the conceptual framework of engineering-specific, Bourdieuian capital. Finally, the final two stages of the instrument development process (empirical testing and validation of the model and instrument of engineering capital) will be introduced as the next chapter of this thesis.

Forming a Conceptual Framework of Engineering Capital

The first stage of the instrument development process requires the development of a conceptual framework to outline the relationship between key concepts in the model of engineering capital. Bordage (2009, p313) refers to this as an exploration of the "ways of thinking about a problem or study, or ways of representing how complex things work". A model of engineering capital is fundamentally a Bourdieuian perspective on inequity in engineering. This can be seen to include three key concepts: the framing of ‘engineering’ as the *scope* of the model, the framing of ‘inequity’ as the *purpose* of the model, and the underlying Bourdieuian framework as the *unifying lens* of the model. The ‘ways of thinking’ for these three concepts within this thesis are outlined in greater detail in the Methodology chapter but will be briefly introduced below.

The definition of ‘engineering’ is the first key element of the conceptual model and relates to the scope of the model and the breadth of its contents. As outlined in Chapters One and Three, ‘engineering’ in this thesis is defined as a domain including specific knowledge, skills, and practices that are related to designing and making, and related to the application of science, technology or mathematics to creatively solve problems. Engineering is understood to share a ‘family resemblance’ with the domain of science: sharing some but not all characteristics and containing distinctive qualities that distinguish the two domains when examined in greater detail (Wittgenstein, 2010). Given the focus of this thesis on secondary school-aged learners, it is necessary to frame ‘engineering’ in an age-appropriate manner. Past literature demonstrates that young learners in the UK conceive of engineering in a notably limited fashion associated with making and fixing (Institution of Mechanical Engineers, 2016; Institution of Mechanical Engineers, 2017; Marshall et al., 2007). However, the profession is seen as well paying (EngineeringUK, 2019; Tindle and Garnett, 2015). Given that the engineering capital model resulting from this conceptual framework will focus on young learners it is necessary for a simplistic definition of engineering as ‘designing, making and fixing’ be included within the definition of engineering in this framework. Although this will be less sophisticated than framings of engineering within higher education or professional contexts it is appropriate for the target population the model addresses. Some secondary school-aged individuals may possess a more sophisticated understanding of engineering – which itself demonstrates an inequity in engineering – however to depend on such a definition would alienate a significant portion of the population and render an exploration of inequity impossible. The conceptualisation of engineering must therefore be sufficiently flexible to acknowledge the distinctions in understanding for this concept. This conceptual ‘way of thinking’ about engineering is central to the development and interpretation of the engineering capital model development process.

The second element of the conceptual framework relates to ‘inequity’ and is the way of thinking about the ‘purpose’ of an engineering capital model. Within this thesis inequity is understood as entrenched patterns of access, participation, success and representation within the engineering domain. This is considered to be a social injustice, facilitating ease for some and difficulty for others that, over time, acts as a selective influence determining entrenched and reproduced patterns of inequity in engineering.

Economic ramifications are also noted resulting from an insufficient number and restricted demographic profile of engineers (EngineeringUK, 2018). Engineering inequities in the UK are recognised to affect gender, ethnic, and social class representation, skewing to a dominant profile of white males from more privileged economic backgrounds (EngineeringUK, 2018; 2018a; 2018b). These inequities are established as multifaceted and intersectional. However, this framing of inequity is also acknowledged as superficial: relating to group categorisation (e.g. white, or male, or middle class) but lacking a deeper understanding of the 'social mechanics' underlying these group differences. From an intersectional perspective, inequity is recognised as a nuanced and sophisticated phenomenon. It is also acknowledged that inequity is context dependent: given the empirical focus on secondary school-aged young people in this thesis it is acknowledged that the context of engineering inequity for this group will differ from the context for adults. Engineering inequity amongst adults may relate to the number of engineering employed individuals or frequency of advanced qualifications for engineering amongst the adult population. These ways of contextualising engineering inequity would not be compatible for younger individuals. Instead, within this thesis, engineering inequity is contextualised in relation to future orientation towards engineering education or careers. These aspirations for engineering offer an age-appropriate perspective on inequitable trajectory for engineering that ties to both a social justice and economic view of inequity covering both fair access to and uptake of education and careers in engineering. Aspirations for engineering, representing orientation towards engineering trajectories, can be considered to be an early stage of the engineering pipeline through which inequities can manifest. Such aspirations for engineering are acknowledged to be inequitable, validating this positioning (EngineeringUK, 2021; Hutchinson & Bentley, 2011). These considerations on engineering inequity collectively shape the design, objectives, and implementations of the engineering capital model.

The final key concept within the conceptual framework relates to the Bourdieuian perspective adopted to serve as an investigative lens on engineering inequity. As noted earlier, contemporary understanding of engineering inequity can be criticised as dominated by shallow group descriptions (e.g. gender, ethnicity, class) that are limited in their insight. Bourdieu's perspective offers the concepts of habitus, capital and field as a more sophisticated lens on inequity that accesses greater nuance of the 'social mechanics' underlying these shallow group descriptions. In this way the Bourdieuian perspective is adopted in this thesis as an understanding of the *process* of inequity and not simply a description of the resulting patterns of observable access, participation, success and representation within engineering. Capital is adopted in particular from this toolkit and defined as a resource that is valuable, can be accumulated, and can be used to access other forms of value (Bourdieu, 1983; Bourdieu, 1986). It is understood to be socially stratified and tied to patterns of power in a manner that results in the powerful dictating the value of capital, and through a process of self-validation, perpetuating the value of their own resources and diminishing the value of the resources of others. This acknowledges that the value of capital is socially determined but will follow existing patterns in an inequitable fashion. The concept of capital thereby extends beyond the individual to also relate to wider societal structure – bridging an objective societal structure with a subjective individual experience within that society.

Many forms of capital can be considered in this manner including varied forms of cultural and social capital as introduced in formative Bourdieuian literature. However, the adoption within this thesis acknowledges criticisms of the traditional Bourdieuian framework as outdated (developed decades ago in a now changed social and cultural context) and focused on artistic dispositions and social class (which are reductive and lack an intersectional consideration) (Bennett et al., 2009; Prieur & Savage, 2013). Therefore, within this thesis the capital concept will be recognised as 'relative' and not 'absolute' in its relationship to Bourdieuian source materials (Prieur & Savage, 2013). It is adopted in a contemporary manner, validated by usage by Archer et al. (2015) and others (Bennett et al., 2009). This understanding of Bourdieuian capital will recognise that cultural capital can change (whereas the traditional Bourdieuian view implies a more robust relationship in line with the social reproduction of society), and that capital can be considered in specific contexts such as science or engineering (whereas the traditional Bourdieuian view was focused on generalised social class reproduction and general educational advantages). In these ways, Bourdieuian thinking is adopted not as a distinct dictation of how society is but rather as a perspective on how distinctions in society might be investigated and framed.

These understandings of engineering, inequity and Bourdieuian capital provide a framing to guide the development of the engineering capital model. Each subsequent stage of the development process will involve navigating these concepts and will influence the final product of an engineering capital model. Having framed these concepts, it is next necessary to move to the second stage of Archer et al.'s (2015) instrument development process and formulate a theoretical model of engineering capital.

A Theoretical Model of Engineering Capital

The next stage of Archer et al.'s capital instrument development process involves the development of a theoretical model of capital. Wider literature is synthesised using the conceptual framework as a guide to interpreting and integrating forms of Bourdieuian capital in relation to engineering inequity. This is a critical stage where the general notion of a domain-specific model of capital becomes a specific, articulated model of capitals for engineering. However, it is important to recognise that the model formed through this process is only one example of a domain-specific model of capital: whilst Archer et al.'s (2015) science capital model is now well known it would be possible to form a different model of science capital if other forms of capital for science were collated. The precise forms of capital chosen to include within the model of engineering capital are highly deterministic to the subsequent model formed in the next stages of the instrument development process.

Noting the lack of previous Bourdieuian examinations of engineering inequity this first model of engineering capital will draw on the forms of capital included within Archer et al.'s science capital model. These forms of capital will be examined in relation to engineering to determine their relevance and utility to an engineering capital perspective. This decision is supported by the previous indications, outlined in Chapters Two and Four, that the forms of capital within the science capital model (such as literacy, dispositions, or social contacts) should apply to engineering. These forms of capital can also be seen as fundamental and natural choices for inclusion in a model of capital for younger learners. Adopting this approach to forming the first theoretical model of engineering capital would also allow a more direct comparison between the product of this development process and science capital to further identify distinctions between capitals and inequity in these domains. Further forms of capital that may relate to the engineering domain will be examined later in this thesis as a further iteration of engineering capital; thus, acknowledging that this first model and instrument is only one possible iteration of engineering capital.

In the following sections, past literature is examined through the conceptual lens of Bourdieuian capital to identify forms of engineering capital. These forms of capital are aggregated to develop a theoretical model of 'engineering capital'. Three forms of cultural capital will be examined (engineering literacy, engineering attitudes, knowledge of engineering pathways), followed by two forms of social capital (knowing an engineer, talking with others about engineering) and finally two forms of practice through which capital may be acquired (consumption of engineering media, participation in out-of-school learning contexts).

Engineering Literacy

The contemporary study of literacy acknowledges that knowledge and capability can be examined in many specific contexts representing 'multiple' or 'disciplinary' literacies tailored to given domains (Shananhan et al., 2016). This expands beyond traditional linguistic framings of literacy addressing knowledge exchange in reading and writing (Indrisano & Chall, 1995). Achievement, qualification or success are important aspects of literacy, determining an individual as ‘literate’ or ‘illiterate’. The expansion of the concept of literacy beyond reading and writing necessitates a widening of the standards of ‘literacy’ given that a ‘literate’ judgement is dictated by the nature of competency in a domain. In some domains a ‘literate’ judgement may go beyond knowledge to include practices, processes, and ways of knowing or doing. A more contemporary and domain-specific definition of literacy would therefore be: the possession of knowledge, skills or understandings determining capacity for competent performance within a domain.

Wider literature acknowledges differing literacies for science, technology, engineering and mathematics. Science literacy is defined by Archer et al. (2015, p929) as “scientific knowledge, skills, and an understanding of how science ’works’ and the ability to use and apply these capabilities in daily life for personal and social benefit”. Technology literacy is argued to relate not only to a developed knowledge or skilful use of technology but also a critical understanding of the shaping influence of technology in the world (Dakers, 2006). Mathematics literacy is defined as a “knowledge to know and apply basic mathematics in our everyday living” and a “broad understanding and appreciation of what mathematics is capable of achieving” (Ojose, 2011, p89). Each of these domain-specific definitions of literacy identify the importance of knowledge, skills and, to some degree, a standard of ability in the domain. An awareness of the lived experience or the role a domain plays within society is also common in such contemporary framings of literacy demonstrating that the concept of literacy goes beyond individual ability to also relate to wider societal context.

Although noted to be lesser considered than other STEM literacies, attempts to define engineering literacy are present within the literature (Krupczak et al., 2012). Both Krupczak et al. (2012) and Chae et al. (2010) approach a definition of engineering literacy through comparison with other STEM domains – Krupczak et al. focusing on distinctions, whilst Chae et al. focus on similarities between literacies. Krupczak et al. (2012) define engineering literacy in contrast to technological literacy, arguing that literacy in engineering is more focused on the process of creation or transformation and is more concerned with ‘making’ than wider societal implications of these made products. Despite adopting a differing approach, Chae et al (2010) also define engineering literacy as a process involving knowledge and skills and in terms of societal impact. This further aligns with the definition of Daugherty et al., (2021) who also acknowledges the ability to succeed in knowledge, skills and societal understanding of engineering. Arguably the most sophisticated and detailed conceptualisation of engineering literacy within contemporary literature is that of Grubbs et al. (2018). Grubbs et al. identify three aspects to engineering literacy: knowledge of engineering (both fundamental sub-domains of engineering such as electrical or chemical engineering and technical knowledge of engineering processes), engineering skills (such as ‘designing under constraint’ and ‘using tools and materials’), and engineering habits of mind (such as ‘systems thinking’ and ‘creativity’) as the ways of thinking and doing as an engineer. Grubbs et al. explore each of these three elements in depth identifying a range of examples of how an engineering literacy can be determined.

Each of these approaches to engineering literacy acknowledge the importance of competence in knowledge, skills and ways of doing and being an engineer in the real world. Unsurprisingly these conceptualisations of engineering literacy do focus more on the skills and practices compared to other, more theoretical/less practical domains of STEM. Within this thesis the definition of engineering literacy is: a sufficient possession of engineering knowledge, skills and ways of ‘thinking’ and ‘doing’ engineering – with a particular focus on the processes and practices of engineering and their resulting societal impact.

This defined concept of engineering literacy is consistent with our conceptual framework in relation to ‘engineering’, ‘inequity’ and ‘Bourdieuian capital’. First, this engineering-specific perspective on literacy meets the framing of engineering within this model as a distinct domain. Second, engineering literacy is established as inequitable within past literature favouring those who are male, from Asian ethnic groups, and from more privileged socioeconomic backgrounds (EngineeringUK, 2022; Hutchinson & Bentley, 2011). Inequities in engineering literacy are also acknowledged to differ from inequities in more knowledge-based, theoretical STEM subjects resulting in greater equity in engineering literacy amongst those who are less academically gifted or those with additional educational needs due to the more active, practice, material qualities of engineering learning (Roth, 2017). Finally, engineering literacy is compatible with the Bourdieuian perspective as a form of embodied cultural capital. Cook-Gumperz (2006) drew on the Bourdieuian perspective to highlight that literacy is socially determined as a subjective judgement of what constitutes a standard of ‘literate’ within a domain and what constitutes value within the development of literacy. This is compatible with the definition of engineering literacy adopted in this thesis if the determination of competence and particular contents (knowledge, skills, and practices) are recognised as socially determined rather than objectively true. The inclusion of the ‘ways of thinking and doing engineering’ reflect Bourdieu’s position on embodied cultural capital as relating to both thinking and embodying, or: “long-lasting dispositions of the mind and body” (Bourdieu, 1986, p17). The knowledge and skills of engineering within engineering literacy can be framed as forms of embodied capital as resources that may benefit a young people in their consideration of and trajectory towards the engineering domain. A young person possessing an understanding of the language of engineering or a practiced skill at designing or making will possess a resource that eases their access to and performance within an engineering context. The benefits of this resource and its socially determined worth determine its value. Contemporary examinations of cultural capital validate this relationship between cultural capital and skill development (Breinholt, 2020). We can thereby acknowledge that engineering literacy is consistent with the conceptual framework and a valid addition to the theoretical model of engineering capital.

Engineering Attitudes

From a psychological perspective, attitudes can be understood as affective-cognitive positions developed over time representing how an individual values an 'attitude object': any abstract concept, physical object, experience, individual or group (Eagly & Chaiken, 2007). Attitudes are fundamental to cognition and can be examined in any context or for any attitude object. Attitudinal considerations might include interest, curiosity, enjoyment, anxiety, or disgust (Fredricks & McColskey, 2012; Izard, 2011). Attitudes for STEM domains in the UK are acknowledged to be widely influenced through systematic, school, individual and external factors (Bennett et al., 2013). Attitudes endure in a relatively stable manner but are subject to change over time and apply in response to contexts – and thereby shape interpretation of future experiences and responses (Schwartz & Bohner, 2001).

A wealth of attitudinal positions on engineering are acknowledged in contemporary UK-based literature. Secondary school-aged learners are noted to find engineering less important to adult life (73% positive response) than science (86%) or mathematics (97%) (Hutchinson & Bentley, 2011). Only 22.4% of a sample of Year 10 students were interested in engineering industries (Hutchinson & Bentley, 2011). Further samples confirm this greater positivity towards science, technology and mathematics (EngineeringUK, 2019). The attitudes of parents and teachers are also established with 90% of STEM secondary teachers and 69% of parents holding positive views of engineering, though some negative attitudes are also noted with 31% of teachers viewing STEM careers as insecure and 28% viewing the domain as difficult (EngineeringUK, 2019; EngineeringUK, 2021a).

Engineering attitudes are consistent with the conceptual framework of engineering capital. First, attitudes can relate to specific domains and therefore can be examined in relation to engineering as defined in this thesis. Second, engineering attitudes are recognised as inequitable within the UK with boys, those from non-white ethnicities and those with more educated parents holding more positive attitudes towards engineering (EngineeringUK, 2021). Finally, attitudes are a relevant element of the Bourdieuian perspective and a form of embodied cultural capital. This psychological framing of attitudes (affective-cognitive positions developed over time and in response to experience and which shape interpretation of future experience) is consistent with the Bourdieuian concept of habitus: “lasting dispositions, or trained capacities and structured propensities to think, feel and act in determinant ways” (Wacquant, 2005, p316) that are “not fixed or permanent, and can be changed under unexpected situations or over a long historical period” (Navarro, 2006, p16). The active and enduring influence of attitudes/dispositions is positioned by Bourdieu as shaped by past experience and society; and in turn shapes subjective experiences to perpetuate the dispositions found within society (Bourdieu, 1984). It is reasonable to consider that the acquisition of positive attitudes towards engineering would support young learners in aspiring to engineering trajectories in education or employment. Engineering attitudes/dispositions are thereby a valid element to include within the theoretical model of engineering capital.

Knowledge of Engineering Pathways

Knowledge of a professional domain, its value, and the utility of qualifications for this domain are acknowledged to influence the decision making of young learners who are deciding their future (Julien, 2004; Super et al., 1973). Examinations of career knowledge have identified that less than half (48.5%) of young learners recognise the potential for engineering qualifications to lead to good jobs (Hutchinson & Bentley, 2011). Parents and teachers are acknowledged as key sources of careers guidance in the UK, yet the confidence of these groups is poor with only 32% of parents and 45% of teachers confident in their ability to give careers guidance for engineering roles (EngineeringUK, 2019; EngineeringUK, 2020). An ‘informational distance’ is acknowledged by UK secondary school STEM teachers which contributes to this lack of confidence (Watermeyer et al., 2016). Access to such guidance or understanding of the value and pathways of engineering careers can thereby be understood to be inequitably distributed.

Knowledge of engineering qualifications and their value is consistent with the conceptual framework of engineering capital. The existence of engineering-specific qualifications enables an engineering-specific focus. Such knowledge and value is also recognised as inequitable with those in higher social grades in the UK significantly more likely to know the steps to become an engineer (64%) compared to those in lower grades (50%) (EngineeringUK, 2020a). This knowledge and valuing of engineering qualifications can also be considered a form of institutionalised cultural capital, and therefore is compatible with the Bourdieuian perspective. Knowledge and valuing of engineering qualifications can be considered to be an age-appropriate framing of institutional capital for young learners who will not yet possess advanced forms of institutional capital such as degree-level qualifications. This is consistent with formative Bourdieuian literature which acknowledges that knowledge of qualifications and educational trajectories differs by social class (Bourdieu and Passeron, 1979). An understanding and valuing of engineering qualifications is therefore a valid addition to the theoretical model of engineering capital and its purpose of understanding engineering aspirations.

Knowing an Engineer

Social forms of capital can also be considered within the Bourdieuian perspective and in relation to engineering inequities in the UK context. Bourdieu framed social capital as "the sum of the resources, actual or virtual, that accrue to an individual or a group by virtue of possessing a durable network of more or less institutionalized relationships of mutual acquaintance and recognition" (Bourdieu & Wacquant, 1992, p119). It is possible to consider the benefit of possessing access to an engineer within an individual's social network and the value that knowing an engineer might bring. Past literature demonstrates the impact of social relationships on socialised learning and learner aspirations (Cheryan et al., 2011). Examinations of international datasets reinforces the benefits to STEM learning mediated through knowing science-role employed individuals (Zhang, 2021). Career decision making literature reveals that in the UK a son is 72% more likely to work in an occupation if their father is currently employed in that role (Bello & Morchio, 2022). This influence is acknowledged as multifaceted, involving comparative advantage to the child, social contacts and changed preferences (Bello & Morchio, 2022). In the UK context, this is valid for knowing an engineer with 8.6% of engineers in one sample stating that they had an engineer for a parent – a higher rate of influence than many other careers examined in the study (Laurison & Friedman, 2016). Further research has acknowledged the importance of knowing an engineer to patterns of engineering study in the UK (Takruri-Rizk, et al., 2008). The positive effect of possessing an engineer parent is acknowledged beyond the UK with research in US settings suggesting a fundamental benefit to such a social relationship (Plasman et al., 2021). A social connection with an engineer can therefore be seen to correlate with a positive influence on trajectory towards engineering, though understanding of the precise mechanics of this influence is limited.

The social influence of knowing an engineer is compatible with the conceptual framework of engineering capital. It is, firstly, compatible with the engineering-specific structure of engineering capital, relating directly to the engineering domain through knowing an engineer. Knowing an engineer is also compatible with engineering inequity given that participation with engineering, and therefore the distribution of engineers throughout social networks, favours certain groups (male, white, socioeconomically privileged). It is therefore reasonable to expect that the resource of knowing an engineer is stratified in the UK. Within parental occupation literature it is acknowledged that maternal occupation is impactful, however in the context of knowing an engineer this must be acknowledged as a particularly uncommon (and therefore inequitable) resource given the low rates of female engineers in the UK (Korupp et al., 2002; Sikora & Pokropek, 2012). Finally, knowing an engineer clearly aligns with the Bourdieuian perspective as a form of social capital. Within this thesis social capital is understood to be "the sum of the resources, actual or virtual, that accrue to an individual or a group by virtue of possessing a durable network of more or less institutionalized relationships of mutual acquaintance and recognition" (Bourdieu & Wacquant, 1992, p119). Knowing an engineer represents a social relationship through which an individual may be able to access the resources of that engineer, for example providing knowledge of how to act like as engineer (embodied cultural capital), providing guidance on how to navigate the trajectory to become an engineer (institutional cultural capital) or providing access to further individuals who are active within engineering (social capital). These resources do not need to be explicitly outlined or identified, rather the potential for access to these resources is sufficient for the resource to be acknowledged as a form of capital for engineering. The influence of knowing an engineer is not well established in the UK context, however theoretically this can still be considered a valid addition to a theoretical model of engineering capital.

Talking with Others About Engineering

'Talking with others about engineering' can be considered a further form of social capital for engineering. This form of social capital considers how an individual engages in communication with others around the subject of engineering. Social interactions are recognised as related not only to the development of knowledge but as a vital element of learning as a process (Daniels, 2008). The direct impact of social interaction to learning is recognised such that distinct pedagogical practices have been developed around this integral process such as peer learning or reciprocal learning practices (Boud et al., 1999; Kayi-Aydar & Miller, 2018). Whilst integral, the benefits of social interactions on learning are recognised to be complex, with factors such as attentiveness of the conversational partner influential in shaping the resulting benefit of social interaction (Pasupathi & Rich, 2005). The consideration of social interaction for engineering is valid given past identification that such interactions support engineering learning and greater recall following social interactions in learning contexts (Benjamin et al., 2010). Past research conducted in the US has recognised the positive impact of STEM-focused social interactions for STEM career aspirations supporting the potential impact of engineering social interactions on engineering trajectories in the UK (Dou et al., 2019).

The influence of social interactions concerning engineering can be acknowledged as compatible with the conceptual model of engineering capital. First, the engineering-specific content of these social interactions meet the conceptualisation of engineering as a distinct subject area. Second, the differing levels of knowledge and attitudes for engineering acknowledged in the engineering literacy and engineering attitudes subcomponents outlined above suggest that the contents of social interactions will differ between groups. This is also suggested by differing levels of knowledge of engineering pathways and confidence in providing careers guidance amongst parents and teachers. Whilst no substantial body of literature has examined the contents of engineering social interactions amongst young learners in the UK it is logical to expect that the underlying differences in knowledge, attitudes, and confidence in communication would result in unequal distributions of this form of capital. Finally, the inclusion of social interactions for engineering is also compatible with the underlying Bourdieuian lens within the conceptual framework of engineering capital as a form of social capital. Social interactions represent a fundamental method for young learners to access the capital within their social networks, aligning with Bourdieuian social capital (Siisiainen, 2003). Talking with others about engineering may thereby represent both a social capital and method for acquiring cultural capital for engineering.

Consumption of Engineering Media

The ways in which capital are developed, including contexts that act as sources of engineering capital or represent inequitable practices tied to engineering aspiration, can also be considered within a Bourdieuian perspective on engineering inequity. These behaviours and practices may not be forms of capital but can be acknowledged as related to the acquisition of capitals for engineering. The inclusion of such behaviours and practices by Archer et al. within the science capital model was valid and bridged the complicated concept of Bourdieuian capital to tangible lived experiences in real world contexts to support the relevance of the capital perspective.

Media consumption is such a practice that may be considered a source of capital for engineering. The consumption of media is acknowledged to produce positive impacts on young learners including the development of interest and knowledge (Levine et al., 2021; Maier et al., 2014). This consumption is recognised as a social phenomena with parents acting as both gatekeepers and co-learners with their children, with some past findings suggesting that the benefits of media consumption are a two-stage process involving mediation through parental figures (Bonus, 2021; Sheehan et al., 2018). However, little literature has examined the impact of engineering media consumption on young UK learners. Wider literature from overseas and for those in tertiary education demonstrate that consumption of STEM media is predictive of later STEM career intention (Dou et al., 2019) and that the use of engineering games supports engineering learning (Coller & Shernoff, 2014). Despite relating to wider contexts beyond secondary school learners in the UK such findings do suggest that the benefits of media consumption outlined in general literature are relevant to the context of engineering and therefore may also be relevant to UK samples. Examinations of media consumption habits within the UK highlight the high rate of access to media amongst secondary school aged learners with 99% of one sample possessing internet access in the home and 50% of participants using this access to learn new skills demonstrating the potential for engineering capital development (Ofcom, 2022). This same examination noted that patterns of participation are varied between social groups demonstrating the potential for inequitable interaction with engineering media (Ofcom, 2022).

Despite the relative paucity of research examining engineering media in the UK context, the relevance of engineering media consumption can be considered in relation to the conceptual framework of engineering capital. The engineering media consumption subcomponent is both engineering-specific and aligned to inequity given recognition that media consumption is an inequitable practice (Lindell, 2020; Ofcom, 2022; Yates et al., 2015). Media consumption can also be understood as a dominant form of cultural consumption and is therefore highly relevant to the Bourdieuian perspective which considers cultural practices and a socially determined judgement of ‘taste’ which guides stratified patterns of consumption. Not only might we consider the consumption of media influenced by these socially stratified tastes, which are established as inequitable in the case of media consumption (Yates et al., 2015), but media consumption can also be considered as a vehicle for access to cultural capital. It is reasonable to expect that the consumption of engineering media may both be supported by and further develop embodied cultural capitals for engineering such as engineering knowledge or engineering attitudes amongst participants. It is logical to expect that an engineering television programme will provide knowledge or that an engineering game is designed to provide opportunities for design thinking and skill development. The relevance of media consumption to the Bourdieuian perspective is further supported by the recognition that social relationships can mediate the consumption of media and its influence, such as parents acting as a gatekeeper or co-learner/interpreter of media for their children. This is consistent with the Bourdieuian understanding of the primary habitus and the influence of close social links to the reproduction of inequity within society. In these ways the consumption of engineering media is relevant to a Bourdieuian examination of engineering inequity and a valid element for inclusion within the engineering capital model.

Engineering Out-of-School Learning Contexts

Out-of-school engineering learning contexts represent a further set of practices in which capitals for engineering may be acquired. Such contexts may include interaction with formal learning spaces such as museums or maker spaces, extracurricular or curricular-mapped experiences such as after school engineering/STEM clubs or visits from engineering engagement and outreach teams, or personal experiences within an individual's home life such as hobbies or interests. Out-of-school learning contexts may have a greater significance to the domain of engineering given the relative lack of engineering within the UK national curricula and the science-dominated focus of 'STEM learning' (Tomei et al., 2013). For the domain of science out-of-school contexts can be seen as an additional resource, but for engineering these represent a dominant context in which learning for engineering can take place. Engineering out-of-school learning contexts are supported, developed and delivered by many stakeholders in the UK, including specialised organisations such as Primary Engineer (Primary Engineer, 2022) who deliver engineering curricular-mapped experiences to primary and secondary-aged learners.

Engineering out-of-school contexts are acknowledged to benefit participants, with 'making' focused out-of-school experiences developing knowledge, skills, and ways of being an engineer (or, in other words, engineering literacy) (Petrich et al., 2013; Shanahan et al., 2016). Engineering out-of-school activities are also noted to support the development of identity for engineering (McVee et al., 2017) as well as wider skills such as mathematicss learning, field experience and the development of team working skills (Denson et al., 2015). These developments might be understood as the acquisition of forms of embodied capital supporting participation within the engineering context.

Engineering out-of-school learning experiences are a valid addition to the engineering capital model, consistent with the outlined conceptual framework. An examination of engineering-specific contexts meets the criterion of 'engineering' within the framework, and wider literature on out-of-school learning contexts recognises that such experiences can be inequitably participated with favouring those of certain ethnic, socioeconomic or geographic location (Dawson, 2012; Department of Culture Media and Sport, 2011; Falk et al., 2015). The consideration of out-of-school learning contexts can also be seen to align with the Bourdieuian capital perspective, which recognises the socially stratified nature of practices that result in inequitable access and participation. The same social dynamics that see classroom contexts institutionally favour those with greater capital may also apply to informal learning contexts. The work of Gathings and Peterman (2021) demonstrated that the development of science capital through science festival contexts was inequitable with STEM minority groups (women/girls, BAME groups) gaining more science capital than others. Participation with out-of-school learning contexts may in this way be seen as a practice that provides access to valuable capital for engineering but in an inequitable manner. Little consideration of engineering out-of-school UK learning contexts is present within the literature, highlighting a need to further examine this topic from a Bourdieuian perspective. Theoretically, however, it would be a valid addition to the engineering capital model.

The Theoretical Model of Engineering Capital

Each of the seven subcomponents of engineering capital identified above can be understood as either forms of capital or contexts through which capital can be acquired in the engineering domain. The collection of these subcomponents into a singular model of engineering capital represents a cross-cutting synthesis of elements relevant to engineering inequity. In particular, the subcomponents represent an array of forms of Bourdieuian capital for engineering including three forms of cultural capital (engineering literacy, engineering attitudes, and knowledge of engineering pathways), two forms of social capital (knowing an engineer, talking with others about engineering) and two collections of behaviours and practices through which capital may be developed (consumption of engineering media, engineering out-of-school learning contexts). The inclusion of varied forms of capital, including both cultural and social capital, offers a strong link between the model and its Bourdieuian underpinning of inequity whilst the inclusion of varied behaviours and practices for engineering ensures a relevance between the contents of the model and the lived experience of the individuals it attempts to understand.

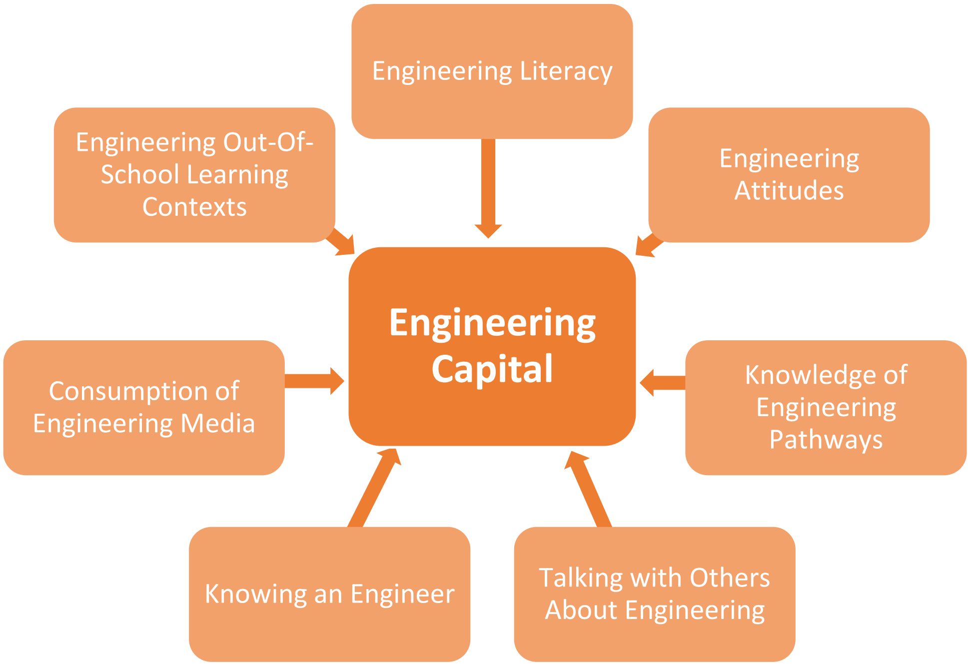

Figure 5.01: The engineering capital model and its seven underlying subcomponents.

As noted in this theoretical examination little literature has examined the engineering domain from a Bourdieuian capital perspective for the UK and its young learners. However, the strong conceptual framework developed in this chapter facilitates the adoption and integration of non-Bourdieuian sources through a rigorous examination. The seven subcomponents of engineering capital outlined above are theoretically sound forms of Bourdieuian capital for engineering despite the background literature of these subcomponents not always examining these factors from a Bourdieuian perspective. Drawing on this literature it is reasonable to expect that these seven subcomponents are inequitably experienced in the UK and are relevant to understanding how engineering trajectories are formed resulting in the acknowledged patterns of engineering education and career inequity.

The decision to examine these seven subcomponents was informed by the structure of the science capital model which had established these forms of capital as relevant to domain-specific understandings within specific capital contexts. As established in Chapter Two the examination of these subcomponents for science may not relate to the engineering domain, but the theoretical model outlined above establishes the theoretical relevance of these subcomponents if approached in an engineering-specific manner. Empirical examination of the theoretical model is necessary to establish its ecological validity as a perspective on engineering inequity. The seven subcomponents included in this theoretical model are not an exhaustive list of forms of capital for engineering. Other forms of capital could also be considered in relation to engineering, such as linguistic capital (examining the linguistic competence of the individual in relation to the engineering context), familial capital (examining how engineering fits within the local community and family context of an individual), or navigational capital (understanding how to navigate the sorts of engineering contexts a secondary school-aged learner may encounter). Past literature indicates the relevance of such forms of capital to the Bourdieuian context and may also be valid for the engineering context (Yosso, 2005). These subcomponents were not included in this initial theoretical model as, pragmatically, this would have overly complicated the development of the model. Though not considered in this first formation of the engineering capital model they may represent valid additions in subsequent models explored in this thesis in recognition that the theoretical model outlined for engineering capital in this chapter is only one possible model and that ongoing testing and improvement is an established stage within the instrument development process adopted in this thesis. The seven subcomponents included in this first model of engineering capital are sufficient to provide a rich perspective on engineering inequities and examine the potential for a valid theoretical and empirical model of capitals for engineering.

The theoretical model outlined in this chapter offers a deep perspective on engineering inequity. Drawing on wider literature, reinterpreting this through a Bourdieuian lens and unifying these considerations within an aggregated structure offers a nuanced perspective on engineering inequity. This approach contains greater detail and ecological validity than existing framings of engineering inequity that are often simplistic descriptions of frequencies and representation by socioeconomic groups (e.g. gender, ethnic, or class groups). The theoretical model of engineering capital considers the underlying social mechanics of influence that push or pull individuals in relation to engineering. This deeper examination of engineering inequity offers greater complexity in understanding the underlying capital structure of engineering access, participation, representation and success. The theoretical model offers a structure to then examine engineering capital in empirical terms to validate this approach and form instruments to maximise the utility and benefit from this work.

Conclusions

Having disproved the value of utilising science capital to understand engineering inequities in previous chapters it was next considered whether Archer et al.'s instrument development process may represent a valid approach to developing a novel engineering capital perspective. Little or no previous literature has examined science capital as an instrument development process. A critical analysis of this process identified it as valid for adoption within this thesis to create a domain-specific model of capital for engineering. This contributes an understanding of how Bourdieuian capital may be rigorously applied to understand patterns of inequity in novel contexts.

The first two stages of this four-stage instrument development process were then completed to produce a conceptual framework and theoretical model of engineering capital. This model aggregated a wealth of past literature under a Bourdieuian interpretation to develop a perspective of capitals for engineering in the UK. This development supported the validity of applying a Bourdieuian lens to the challenges of engineering inequity. The resulting theoretical model of engineering capital represents an advancement in understanding that unifies distinct bodies of literature to better understand the nuances of engineering inequity amongst young learners.

In the next chapter the third stage of the instrument development process will be completed. The theoretical model of engineering capital will be transformed into a concise, validated quantitative instrument capable of measuring the engineering capital of young learners. An empirical structure of engineering capital will facilitate measurement and investigation of engineering inequity in an empirical methodology to better understand the engineering inequities amongst young UK learners. This development will support greater understanding of engineering inequity and see the novel theoretical perspective developed in this chapter applied within a real-world context.

CHAPTER SIX: CREATING AN ENGINEERING CAPITAL INSTRUMENT

Introduction

In previous chapters a novel theoretical model of engineering capital was developed through a reinterpretation of past literature under a Bourdieuian framework. Whilst theoretically useful this model possesses a limited practical utility in efforts to build greater understanding of engineering inequity in real world contexts. In the following chapter the third stage of the adopted instrument development process will be undertaken to create a robust, concise empirical instrument capable of measuring the engineering capital of young learners to support the practical investigation of engineering inequity in the UK. First, seven subcomponent instruments will be developed to empirically measure the engineering capital model. Second, data collected with these instruments will be analysed to confirm the reliability and validity of these measurement tools. Finally, statistical analyses will aggregate and refine the seven instruments to form a shorter, more powerful diagnostic instrument to measure engineering capital.

Creating an Instrument of Engineering Capital

In Chapter Five the first two stages of Archer et al.'s (2015) instrument development process were completed to create a conceptual framework and theoretical model of engineering capital. Through the adoption of a Bourdieuian perspective and the synthesis of past literature a contemporary and novel theorisation of engineering capital was developed. Whilst useful as a theoretical exploration of the forms of capital for engineering that young learners in the UK may possess, this model requires further validation through empirical investigation. In particular, to achieve the objectives of this thesis to better understand and intervene with engineering inequities it is necessary to create an empirical instrument capable of assessing engineering capital.

In this current chapter, the third stage of the instrument development process is undertaken to develop an empirical instrument capable of measuring engineering capital. This stage involves the creation of a quantitative questionnaire drawing on the newly created theoretical model. The questionnaire developed during Archer et al.'s (2015) use of this process drew on existing instruments in addition to the creation of novel items (Archer et al., 2015; Archer et al., 2013; IPSOS Mori, 2011). Drawing on existing items supports the potential criterion validity of the questionnaire developed through this process (McDonald, 2005). Following the questionnaire development data is next collected from the target sample. Finally, participant responses are analysed using Principal Components Analysis, Binary Logistic Regression Analysis and Cronbach's Alpha analysis to refine this larger questionnaire into a concise and effective capital instrument. Benson and Clark (1982) would view this stage as 'quantitative evaluation', whilst Kalkbrenner (2021) would identify this as 'synthesise content and scale development' and 'recruit participants' within their instrument development procedures.

This approach to instrument development is robust, utilising a statistical method of formation that limits subjective judgement and relies on objective measurements to determine the structure of the resulting instrument. Such a data-led approach is valid and ensures that influences not included in the theoretical model, but active within real world settings, can influence the collected data and therefore shape the resulting instrument. This process is suitable for the development of a model of engineering capital. Comparative to the science domain, there are fewer existing instruments of engineering inequity from which to draw on during the formation of this new tool. However, as demonstrated by the 'Archer-style engineering capital' model in Chapter Four, it is possible to adapt questionnaire items from non-engineering contexts to produce a viable instrument for the engineering domain. This process will therefore be adopted to generate an empirical instrument of engineering capital. The development of this instrument would enable a quantitative investigation of engineering capital and achieve the objective of this thesis in building more sophisticated understandings of engineering inequity in the UK.

Chapter Research Methods

Methodology

The methodological approach adopted within this chapter is dictated by the instrument development procedure undertaken in the overall thesis. An empirical approach is adopted in the formation of the quantitative engineering capital instrument. The procedure undertaken by Archer et al. (2015) is utilised to first form an empirical questionnaire based on the theoretical model of engineering capital which is then refined through statistical analyses (Cronbach's Alpha, Principal Components Analyses, and Logistic Regression) to form a final engineering capital instrument. This draws on the conceptual framework and theoretical model outlined in Chapter Five and the philosophical positioning of the thesis project outlined in the Methodology chapter.

Participants

Data was collected from 921 secondary school-aged (11 to 16 years old) learners from ten schools in England and Scotland. As noted in the Methodology chapter, a single point of data collection was adopted for this thesis research project due to the demands of the Covid-19 pandemic. The sample of 921 learners examined in this chapter is the same sample examined throughout the thesis. See Methodology chapter for full outline of sample characteristics and rationale for the selected participant population.

Data Collection Instruments

Seven instruments were developed to empirically examine the seven theoretical subcomponents of engineering capital. These instruments were informed by theoretical literature outlined in Chapter Five and the domain-specific capital measurement instruments developed by Archer et al. (2015). These instruments are outlined below.

Engineering literacy: The engineering literacy theoretical subcomponent relates to the knowledge, skills and ways of 'thinking' and 'doing' present within the engineering domain. This form of cultural capital is understood as deeply important and a key feature of a domain-specific model of capital (Archer et al., 2015). A quantitative instrument was developed to measure this subcomponent drawing on Archer et al.'s instrumentation and informed by wider theoretical literature on engineering literacy (Chae et al., 2010; Huffman et al., 2018; Krupczak et al., 2012). These items are outlined in Table 6.01 below.

Table 6.01: Engineering literacy items and response scales.

Item	Response Scale
One or both of my parents know a lot about engineering	-2 to 2 five-point Likert scale
I have learnt a lot about engineering from museums	-2 to 2 five-point Likert scale
Anyone can become an engineer	-2 to 2 five-point Likert scale
I know how to design and make things	-2 to 2 five-point Likert scale
I know quite a lot about engineering	-2 to 2 five-point Likert scale
Engineers need to be imaginative in their work	-2 to 2 five-point Likert scale
I would be confident talking about engineering in lessons	-2 to 2 five-point Likert scale

Engineering attitudes: The engineering attitudes theoretical subcomponent represents an embodied form of cultural capital that shapes how individuals (and their parental figures) perceive and value the engineering domain. A measurement instrument of engineering attitudes was developed drawing on Archer et al.'s science capital instrument and past literature on engineering attitudes in the UK context

(EngineeringUK, 2021; EngineeringUK, 2021a; Hutchinson & Bentley, 2011). These items are outlined in Table 6.02 below.

Table 6.02: Engineering attitudes items and response scales.

Item	Response Scale
One or both of my parents think that engineering is very interesting	-2 to 2 five-point Likert scale
One or both of my parents think it is important for me to learn about engineering	-2 to 2 five-point Likert scale
My family like going to museums	-2 to 2 five-point Likert scale
I like going to museums	-2 to 2 five-point Likert scale
Engineering creates new jobs so more people can have work	-2 to 2 five-point Likert scale
It is useful to know about engineering in my daily life	-2 to 2 five-point Likert scale
Getting young people to understand engineering is important for our society	-2 to 2 five-point Likert scale

Knowledge of engineering pathways: The knowledge of engineering pathways subcomponent relates to the understanding that engineering qualifications hold value and offer utility to their possessor. A measurement instrument of this institutional cultural capital subcomponent was developed informed by literature (EngineeringUK, 2020; EngineeringUK, 2020a; Hutchinson & Bentley, 2011; Watermeyer et al., 2016) and the science capital measurement instrument (Archer et al., 2015). These items are outlined in Table 6.03 below.

Table 6.03: Knowledge of engineering pathways items and response scales.

Item	Response Scale
It is important to understand engineering even if you don’t want an engineering job in the future	-2 to 2 five-point Likert scale
An engineering qualification can help you to get many different types of job	-2 to 2 five-point Likert scale
One or both of my parents have explained to me that understanding engineering is useful for my future	-2 to 2 five-point Likert scale
My teachers explain how engineering qualifications can lead to different jobs	-2 to 2 five-point Likert scale

My teachers have explained to me that understanding engineering is useful for my future	-2 to 2 five-point Likert scale

Knowing an engineer: The knowing an engineer social capital subcomponent relates the potential benefits offered through a social connection to an engineer. A measurement instrument for this subcomponent was developed informed by literature (Bello & Morchio, 2022; Cheryan et al., 2011; Laurison & Friedman, 2020; Takruri-Rizk, et al., 2008) and Archer et al.'s (2015) domain-specific capital measurement instrument. These items are outlined in Table 6.04 below.

Table 6.04: Knowing an engineer items and response scales.

Item	**Response Scale**
Do you know anyone (family, friends or community) who works as an engineer or in a job that uses engineering?	0 to 1 binary yes/no response
If yes: You said you know someone amongst your family, friends or community who works as an engineering or in a job that uses engineering, can you tell us who they are?	0 to 7 scale: 2 points added for parental figure, 1 point added for each of the following multiple choice options selected: Siblings (brothers or sisters), Extended family members (grandparents, aunts, uncles, cousins), Friends, People I know from my community, and other.

Talking with others about engineering: The talking with others about engineering subcomponent represents the social capital offered through social interaction concerning the engineering domain. The measurement of this subcomponent was informed by wider literature (Benjamin et al., 2010; Dou et al., 2019) and Archer et al.'s (2015) empirical instrument. These items are outlined in Table 6.05 below.

Table 6.05: Talking with others about engineering items and response scales.

Item	**Response Scale**
When you are not in school how often do you talk about engineering with other people?	0 to 4 five-point Likert scale
Who do you talk with about engineering?	0 to 4 scale: 0.5 points added for each multiple choice option selected: Friends, Directly from scientists, Directly from engineers, Siblings (brother or sisters), Teachers, Parents or guardians, Extended family members

	(grandparents, aunts, uncles, cousins), People I know from my community, No one.

Consumption of engineering media: The consumption of engineering media subcomponent refers to a behaviour or practice that may support the development of engineering capital. A measurement instrument was developed drawing on wider literature (Dou et al., 2019; Lindell, 2020; Yates et al., 2015) and the Archer et al. (2015) science capital instrument. These items relate specifically to available examples of engineering media within the United Kingdom: as noted in earlier chapters the focus of this thesis lies within the cultural and social context of the UK. This may limit the degree to which the instrument can be applied internationally without amendment, however such an international application would first require a testing to validate the relevance of this instrument to non-UK settings. International applications may benefit from utilising media examples from local settings. These items are outlined in Table 6.06 below.

Table 6.06: Consumption of engineering media items and response scales.

Item	**Response Scale**
How often do you do the following things outside of school: watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.?	0 to 4 five-point Likert scale
How often do you do the following things outside of school: watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.?	0 to 4 five-point Likert scale
How often do you do the following things outside of school: read books or magazines about engineering?	0 to 4 five-point Likert scale
How often do you do the following things outside of school: go online to find out about engineering (e.g. YouTube, engineering websites, play engineering games)?	0 to 4 five-point Likert scale

Engineering out-of-school learning contexts: The engineering out-of-school learning contexts subcomponents explores further contexts through which engineering capital may be developed. This measurement instrument was informed by past literature (McVee et al., 2017; Petrich et al., 2013;

Shanahan et al., 2016) and the Archer et al. (2015) science capital instrument. These items are outlined in Table 6.07 below.

Table 6.07: Engineering out-of-school learning contexts items and response scales.

Item	**Response Scale**
One or both of my parents sign me up to activities outside of school time (e.g. dance, music, clubs)	-2 to 2 five-point Likert scale
How often do you do the following things when you are not in school: go to a museum?	0 to 4 five-point Likert scale
How often do you do the following things when you are not in school: go to a science centre, science museum, or planetarium?	0 to 4 five-point Likert scale
How often do you do the following things when you are not in school: do DIY or help to fix things at home?	0 to 4 five-point Likert scale
How often do you do the following things when you are not in school: get shown how to use tools?	0 to 4 five-point Likert scale
How often do you do the following things when you are not in school: make models (e.g. playing with Lego, painting miniatures)?	0 to 4 five-point Likert scale
How often do you do the following things when you are not in school: do crafts (e.g. knitting, woodwork)?	0 to 4 five-point Likert scale
How often do you do the following things when you are not in school: play video games about designing and/or building (e.g. The Sims, Minecraft)?	0 to 4 five-point Likert scale
How often do you do the following things when you are not in school: program computers (e.g. writing apps, building websites)?	0 to 4 five-point Likert scale
How often do you do the following things when you are in school: go to an after school club that involves engineering?	0 to 4 five-point Likert scale
How often do you do the following things when you are in school: had people visit you in school to teach you about engineering?	0 to 4 five-point Likert scale
How often do you do the following things when you are in school: take an engineering-related school trip?	0 to 4 five-point Likert scale

How often do you do the following things when you are in school: take part in a competition where you design or make something?	0 to 4 five-point Likert scale
How often do you do the following things when you are in school: do school activities where you design or build something (e.g. designing a bridge, making and testing paper airplanes)?	0 to 4 five-point Likert scale
How often do you do the following things when you are in school: take a school trip to a museum?	0 to 4 five-point Likert scale

Engineering aspirations: Engineering aspirations were measured as a dependent variable (DV) for use within later analyses. This instrument also drew on Archer et al.'s approach to contextualising the aspirations of secondary school-aged learners and was informed by further literature (EngineeringUK, 2022; EngineeringUK, 2022a; Hutchinson & Bentley, 2011). These items are outlined in Table 6.08 below.

Table 6.08: Engineering aspirations items and response scales.

Item	Response Scale
I would like to have a job that uses engineering	-2 to 2 five-point Likert scale
I want to become an engineer	-2 to 2 five-point Likert scale
Do you think you might like to work in an engineering-related job in the future?	0 to 1 binary yes/no response
Although it is a long way off, which of the following describes your views?	I would like to study engineering at university, at college/sixth form, after GCSE/National 5s but not A-Level/Highers, I do not want to study any engineering after GCSE/National 5s, None of the above or I don't know

Engineering identity: Engineering identity was also measured as a further dependent variable for use within later analyses. This instrument drew on Archer et al.'s (2015) approach to conceptualising learner identity. These items are outlined in Table 6.09 below.

Table 6.09: Engineering identity items and response scales.

Item	Response Scale
People who are like me work in engineering	-2 to 2 five-point Likert scale
Other people think of me as an engineering-type person	-2 to 2 five-point Likert scale

My teachers have specifically encouraged me to consider studying engineering after GCSE/National 5s	-2 to 2 five-point Likert scale
I don’t think I am clever enough to study engineering after GCSE/National 5s	-2 to 2 five-point Likert scale

Procedure

First, an empirical questionnaire was formed to examine the seven subcomponents within the theoretical model of engineering capital. Adopting pre-validated items from existing instruments was an important element of Archer et al.’s (2015) instrument development process. However, few pre-validated instruments were available to measure engineering inequity generally or specifically through a Bourdieuian lens. Instead, the science capital instrument was adopted and repurposed to instead examine the engineering domain. This approach had previously been successful in the creation of the ‘Archer-style engineering capital’ model in Chapter Four. Many of Archer et al.’s (2015) items had themselves been drawn from previous literature supporting the wider validity of these items. The theoretical model of engineering capital was utilised to support the theoretical validity of these translated empirical items.

Second, building on this theoretical validation statistical analyses were conducted to examine the validity and reliability of the newly created instruments. Principal Components Analyses (PCA) were adopted to examine the simplified structure of instruments and to determine whether this structure aligned with theoretical expectations outlined in the model of engineering capital (Ho, 2013). As noted in the Methodology chapter, Bourdieuian capital is adopted within this thesis as an interpretative tool: the forms of capital examined in these instruments are not positioned as objectively ‘true’ latent variables that exist in society but as theoretically structured interpretations of complex real-world conditions. The use of these instruments is therefore not concerned with identifying an underlying factor structure but instead is concerned with examining how instrument items relate to the created notion ‘engineering literacy’ or ‘engineering media consumption’ positioned by the robust theoretical model. This rules out the adoption of other factor analysis approaches that are concerned with causal structure. Whilst Principal Components Analyses are not sufficiently robust to identify causality in latent factors this method can be used to examine whether items load onto simple singular component structures as a test of dimensionality in relation to Bourdieuian capital interpretations. This adoption is consistent with that of Archer et al. (2015) in the science capital development process. PCA results can be reflected on to confirm the interconnectivity of items and to identify redundancy in instrument structures. Whilst a less robust test of validity than a factor analysis this approach can still support the development of instruments that measure what they intend to measure. Cronbach's Alpha analyses were deployed as an acknowledged statistical method to confirm the internal consistency of the developed instruments (Ho, 2013). Statistical test assumptions were met supporting the use of these tests in all applications.

Next, it was possible to begin the process of aggregation and refinement to create a singular measurement instrument of engineering capital. To do this a further Principal Components Analysis was applied to the items from all seven instruments to examine the dimensionality of the overall instrument and its relationship with engineering inequity. This additional PCA was necessary to examine the interconnectedness of the seven empirical subcomponent instruments and identify redundancy. The PCA procedure utilised a Direct Oblimin rotation to clarify the structure of the resulting model. An oblique rotation, such as the Direct Oblimin, was chosen as this rotation acknowledges that resulting components can be correlated (Ho, 2013). This is expected for the components within this model as they share a common capital underpinning. The resulting components drawn from this PCA were unweighted, treating all components and items equally. This was determined as more appropriate given that patterns of weightings differ in differing samples, representing individual differences. As this PCA was being utilised to form an instrument it was necessary to avoid entrenching the characteristics of this first sample on all later samples using the resulting engineering capital instrument. As per common practice, weaker coefficients identified by the PCA were removed to sharpen the scope of the resulting output. Differing standards exist within the literature with some considering a cut off of 0.3 (Comrey & Lee, 2013; Tabachnick et al., 2007) and others 0.4 (Stevens, 2012). A cut off of 0.4 was chosen for this analysis to be more discerning and selective in including items with the intention of forming a stronger instrument. Statistical test assumptions were met supporting the use of these tests.

Finally, having identified which items were valid for consideration within an engineering capital lens the items used to measure the seven theoretical subcomponents of engineering capital were analysed with a binary logistic regression to identify which items were most influential in determining those with greater or lesser aspirations for engineering. Statistical test assumptions were met supporting the use of these tests. Aspirations were chosen as a proxy indicator of engineering capital given the underlying premise that those with greater engineering capital will be better supported to aspire to engineering trajectories. The premise is supported by the positive association between Archer-style engineering capital and engineering aspirations outlined in Chapter Four. The binary logistic regression identified 11 items which were collated to form an engineering capital measurement instrument. Through this procedure a broad theoretical framework of seven engineering capital subcomponents was empirically structured, examined, and refined to form a compact measurement tool for engineering capital.

Results and Discussion

Confirming the Reliability and Validity of Subcomponent Instruments

It was necessary to confirm that the empirical items developed or adopted to address the seven subcomponents of engineering capital were valid and reliable instruments. This is necessary to ensure that the resulting engineering capital instrument is valid and reliable following the aggregation of its items. To ensure each subcomponent was a strong addition to the overall model it was necessary to run a PCA to examine its dimensionality and utilise Cronbach's Alpha analysis to test its reliability. The results of these tests are outlined for the subcomponents below. See Appendix F for full statistical outputs.

Engineering literacy: PCA analyses examined the dimensionality of the measurement index for this subcomponent and concluded that the item 'Anyone can become an engineer' should be removed from the measure, but that the remaining items form a unidimensional structure that follows the theoretical framing of the subcomponent. A Cronbach's Alpha analysis confirmed that the six-item instrument possessed adequate internal consistency (N=865, a=0.761).

Engineering attitudes: PCA analyses identified a two-component solution focusing on attitudes towards engineering generally or positive enjoyment of engineering learning activities with family specifically, correlated to a R^2=0.303 level. Although not unidimensional these components do follow the theoretical framing of the subcomponent and are a valid addition to the empirical measure of engineering capital. A Cronbach's Alpha analysis confirmed that the seven-item instrument possessed adequate internal consistency (N=867, a=0.802).

Knowledge of engineering pathways: PCA analyses identified a two-component solution focusing on understanding of the participant and understanding of those around the participant, correlated to a R^2=0.371 level. Although not unidimensional these components do follow the theoretical framing of the subcomponent aligning with acknowledged differences in the engineering knowledge of teachers, parents and young people in the UK (EngineeringUK, 2020; Hutchinson & Bentley, 2011; Watermeyer et al., 2016). This instrument is therefore a valid addition to the empirical measure of engineering capital. A Cronbach's Alpha analysis confirmed that the five-item instrument possessed adequate internal consistency (N=863, a=0.762).

Consumption of engineering media: PCA analyses identified a single component including all four items aligning with the theoretical justification of the subcomponent which generalises such media together. A Cronbach's Alpha analysis confirmed that the four-item instrument possessed adequate internal consistency (N=890, a=0.796).

Engineering out-of-school learning experiences: PCA analyses examined the dimensionality of the measurement instrument for this large subcomponent and identified a four-component solution relating to: designing and making experiences, school-related informal learning, home and family-based learning, and digital/computer-based experiences. Whilst not a simple structure this does follow the structure of the theoretical subcomponent which, it should be acknowledged, is broad and unlikely to exist as a unidimensional construct. A Cronbach's Alpha analysis (based on standardised items) confirmed that the 15-item instrument possessed adequate internal consistency (N=852, a=0.810).

The distribution of responses for these items was found to be acceptably normal, with acceptable skew and kurtosis indicating a normal distribution within participant scale responses. This was to be expected as per Central Limit Theorem which states that sample means will be normally distributed if drawn from a sufficiently large sample. The size of this sample (N=921) is sufficiently large to support the normality of distribution of smaller sub-samples such as gender groups within the analyses of this thesis.

Two of the seven subcomponents, 'talking with others about engineering' and 'knowing an engineer', were not able to be reliability and validity tested due to the small number of items used to assess these forms of capital. As more simplistic measures they can be supported with a theoretical rationale for their inclusion in the model – later analyses to form the instrument will remove these items if they are not warranted. The five subcomponents that were examined with reliability and validity tests were all confirmed as justified additions to the engineering capital instrument development process. Only one item ('Anyone can become an engineer') was removed. All five subcomponents were found to be reliable, with Cronbach's Alpha scores between 0.761 and 0.810, and valid with dimensionality of empirical data fitting to the expectations of the theoretical model. Despite many of these items being drawn from the science domain these analyses confirm that the items follow the theoretical structure of engineering capital and are therefore justified as elements of the empirical instrument developed in this chapter. This validates the conclusions of Chapter Two which noted that many of the forms of capital included within science capital were likely relevant for engineering if specifically considered for the engineering-domain.

Principal Components Analyses – Examination of All Aggregated Items

Having confirmed the reliability and validity of the empirical instruments designed to individually measure the subcomponents of engineering capital it was next necessary to aggregate and refine these items to produce a focused instrument of engineering capital. The first step of this process required a further Principal Components Analysis of the collected engineering capital instruments to examine the dimensionality of the overall empirical structure of engineering capital. Interpretation of components generated by this analysis can provide insight on the interaction of subcomponent measures and patterns within the item structure of engineering capital. This analysis included 47 items from the subcomponent and DV instruments. Given the large number of items used within this PCA a Direct Oblimin rotation was adopted to ease interpretation of results.

The PCA resolved to 10 components above an eigenvalue of 1.0, explaining 63.112% of the total variance within the data. Only 773 participants were included within the analysis as a casewise removal of participants (the removal of a participant if any single data point was missing from their entry) was required to ensure all items could be fairly examined. This sample was still sufficiently large to meet the demand for 5 to 10 participants per item (Bandalos & Boehm-Kaufman, 2010). The PCA passed both the Kaiser-Meyer-Olkin test of sampling adequacy (KMO=0.928) and the Bartlett's test of sphericity ($x^2(1081) = 19134.532$, $p<0.001$) indicating that the use of PCA was valid. The ten components were reviewed to form an understanding of what each component grouping of items represented and were then labelled accordingly. These components and their constituent items are outlined in Appendix F. It was, however, necessary to complete further PCA procedures to refine the resulting component structure by removing items that did not load clearly to a component at a 0.4 coefficient level. Eight items were removed following this first PCA, outlined in Table 6.10.

Table 6.10: Items removed within the first all-item PCA.

Item
I know how to design and make things
I know quite a lot about engineering
I would be confident talking about engineering in lessons
When you are not in school how often do you talk about engineering with other people?
Who do you talk with about engineering?
How often do you do the following things when you are in school: do school activities where you design or build something (e.g. designing a bridge, making an testing paper airplanes)?
I don't think I am clever enough to study engineering after GCSEs/National 5s
One or both of my parents sign me up to activities outside of school time (e.g. dance, music, clubs)

Following the removal of these items a second PCA was performed to examine the component structure of the engineering capital instrument. This second PCA again resolved to 10 components explaining 67.388% of data variance, with little difference to the overall structure of the component matrix – though some coefficient values did change. The sample increased to 779 participants as fewer items led to fewer instances of casewise removal of participants. The PCA passed the KMO test of sampling adequacy (KMO=0.913) as well as the Bartlett's test of sphericity ($x^2(741) = 15421.453$, $p<0.001$). The ten components maintained the same structure and labels as within the first PCA though with very minor changes to variances explained by each component. The second PCA results are also found in Appendix F. A third PCA was necessary to remove components that contained fewer than three items as these components are difficult to interpret and most likely to change in meaning in the addition or subtraction of items. This led to the removal of components nine and ten: tentatively titled 'Designing and Making with Technology' and 'Wider Utility of Engineering', including a number of items outlined in Table 6.11 below. A third PCA was needed to account for the change in component structure resulting from these removals.

Table 6.11: Items removed within the second all-item PCA.

Item
How often do you do the following things when you are not in school: play video games about designing and/or building (e.g. The Sims, Minecraft)?
How often do you do the following things when you are not in school: program computers (e.g. writing apps, building websites)?
It is important to understand engineering even if you don't want an engineering job in the future
An engineering qualification can help you to get many different types of job

The third PCA resolved to eight components above an Eigenvalue of 1.000 explaining 66.213% of data variance. The sample size again increased to 786 participants due to fewer casewise removals. The PCA passed both the KMO test (KMO=0.910) and Bartlett's test ($x^2(595) = 14496.568$, $p<0.001$). The eight components remained stable from the first and second PCAs and are outlined in Table 6.12 below. No further PCA was needed following this test as no remaining items needed to be removed. The third PCA therefore represents the final stage of the PCA investigation and the 'simple structure' of engineering capital items.

Table 6.12: Simple structure of eight components produced by the third all-item PCA.

Component Number	Component Label	Variance Explained	Items and Component Coefficients
1	Engineering Career Aspiration	28.758%	Six items: I would like to work in an engineering-related job, but not in an engineering industry (0.771) I would like to have a job that uses engineering (0.761) I would like to have a job that involves designing and making things (0.715) I want to become an engineer (0.695) People who are like me work in engineering (0.685) Other people think of me as an engineering-type person (0.429)
2	Museum Visits	9.505%	Five items: My family like going to museums (0.878) I like going to museums (0.841) Go to museum? (0.804) Go to a science centre, science museum, or planetarium? (0.719) I have learnt a lot about engineering from museums (0.558)
3	Engineering Utility	6.103%	Four items: Engineers need to be imaginative in their work (0.0.854) Engineering creates new jobs so more people can have work (0.849) Getting young people to understand engineering is important for our society (0.735) It is useful to know about engineering in my daily life (0.610)
4	Engineering Curricular-Mapped Experiences	5.713%	Five items: Take an engineering-related school trip? (0.795) Had people visit you in a school to teach you about engineering? (0.643) Go to an after school club that involves engineering? (0.629) Take a school trip to museum? (0.598) Take part in a competition where you design or make something? (0.499)
5	Making and Fixing	4.838%	Four items: Do DIY, or help fix things around the home (0.794) Get shown how to use tools? (0.688) Do crafts, e.g. knitting, woodwork? (0.677)

			Make models, e.g. playing with Lego, painting miniatures? (0.533)
6	Parental Engineering Attitudes	4.173%	Four items: …know a lot about engineering (0.806) …Think it is important for me to learn about engineering (0.764) …Think that engineering is very interesting (0.757) …Has explained to me that understanding engineering is useful for my future (0.751)
7	Teacher Support for Engineering	3.813%	Three items: My teachers have explained to me that understanding engineering is useful for my future (0.894) My teachers explain how engineering qualifications can lead to different jobs (0.873) My teachers have specifically encouraged me to consider studying engineering after GCSEs/National 5s (0.847)
8	Engineering Media Consumption	3.311%	Four items: Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc. (0.756) Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc (0.696) Read books or magazines about engineering? (0.690) Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games? (0.675)

Notably, the component structure generated by this series of Principal Component Analyses differs from the seven theoretical subcomponents identified in Chapter Five. This is not surprising, as the theoretical model is structured according to classifications of capital within the Bourdieuian framework. This is an artificial interpretation of the world, and one that is unlikely to be replicated within real-world data. In reality, these theoretical distinctions are less clear. Some theoretical subcomponents remain intact, such as the theoretical subcomponent of ‘consumption of engineering media’ which is established as component eight. However, others such as ‘engineering attitudes’ are distributed across several PCA components. This does not invalidate the theoretical lens as a tool to structure these influential resources: the PCA components can be used to reflect further on the contents of the theoretical model and the interconnectedness of its subcomponents.

For example, components six and seven are structured around teachers and parents as key influencers within the life of the young person. The Principal Components Analysis identified patterns within the responses of participants which associate these items together. This aligns with past literature that recognises these influencers and, in line with the Bourdieuian framework, supports the underlying influence of parents and teachers within the engineering capital model (EngineeringUK, 2018; EngineeringUK, 2022). This structure supports an interconnectedness of theoretical subcomponents ‘engineering attitudes’ and ‘knowledge of engineering pathways’ through the common influence of parents. Component four was titled ‘engineering curricular-mapped experiences’ due to the school-based focus of its items. This highlights a pattern of consistency within responses to items concerning schools which suggest that school-based characteristics may play a role in shaping the engineering capital of young learners. All of these influences are active within the theoretical model of engineering capital but become clear when the structure of the model is reorganised and simplified according to patterns within response data.

It is also notable that the DV measures included within the PCA aligned to form a single component of engineering aspirations and identity items (component one). This is helpful, as later stages of the instrument development process require a dependent variable and this analysis offers component one as a synthesised unidimensional DV for engineering aspirations and identity.

However, it must be recognised that 12 items were removed from this series of analyses. Examinations show that these items were removed as they did not conform with best practices of data reduction: they did not form components with at least three items or they possessed item coefficient values of less than 0.4 indicating a weak fit to the ten established components. However, vitally, this does not discredit these items as valid considerations of Bourdieuian capital for engineering. These items may have reached the threshold of three connected items and formed components if a small number of further items were introduced, or if items in other components are removed leading to a restructuring of the model. In this way it must be recognised that the PCA is simplifying a structure, not dictating the objective reality of relevance for these items. As a result, these items may still be considered as representative of valid aspects of engineering capital – but not neatly packaged with other items within the questionnaire. These items will therefore still be drawn on in the final instrument of engineering capital.

Overall, this analysis demonstrates that the theoretical model of engineering capital is not the only way in which these forms of capital for engineering can be aggregated and structured. This aligns with the underlying Bourdieuian framework and its positioning in this thesis as a ‘thinking tool’. Through its simplification the PCA process identifies key influences that group item responses within the collected data: teachers, parents, school settings, making and fixing activities, and school contexts are just some of the key components recognised within this measurement of engineering capital. Despite its simplified structure differing from the theoretical model these findings support the interconnectedness and perspective of the engineering capital model contents. This further supports the synthesis of these subcomponent scales to develop a singular measurement instrument of engineering capital.

Binary Logistic Regression Analysis

Having investigated the relevance of items within the engineering capital questionnaire it was next necessary to perform a binary logistic regression analysis to identify which items were most influential in determining high or low levels of engineering capital. This identification would allow the formation of an engineering capital instrument drawing on only the most influential questions to produce a concise and impactful measurement tool. This statistical process was utilised by Archer et al. (2015) in the successful formation of the science capital instrument. A singular instrument for engineering capital is consistent with the aggregating theoretical structure of engineering capital in Chapter Five. Whilst it is possible to distinguish distinct species of capital, such as engineering literacy as a form of cultural capital or knowing an engineer as a form of social capital, these subcomponents must each be recognised as aspects of the larger concept of 'engineering capital'. A singular instrument of engineering capital that can be used to distinguish those with greater or lesser engineering capital is more compatible with this holistic conceptualisation of engineering capital than a multitude of subcomponent-specific instruments. A regression analysis on items from all subcomponent instruments can identify the most influential items within these scales and support an aggregation of influential items into a 'single factor' framing of engineering capital.

A binary logistic regression analysis was utilised to examine 41 items from the seven engineering capital subcomponent instruments. The decision was made to include the items that were removed from the first and second all-subcomponent PCAs as their exclusion was due to not fitting relatively arbitrary maxims for the PCA procedure and not due to a lack of theoretical validity. As noted earlier, PCAs can simplify the structure of examined data but cannot dictate the objective relevance of included items. The items removed from the earlier PCAs can still be understood as theoretically valid additions to an instrument of engineering capital: the item 'I know quite a lot about engineering', for example, is highly relevant to the 'engineering literacy' subcomponent but was removed from the first all-item PCA. Including all removed items within the regression analysis ensures that no relevant item is inadvertently rejected from the resulting instrument created to distinguish those with higher or lower levels of engineering capital.

Binary logistic regression analyses require a dependent variable to which other items can be compared. As no engineering capital instrument yet existed to act as this DV a proxy was required. The PCA component 'Engineering Career Aspiration' was chosen to act as the dependent variable of the regression analysis. The use of 'Engineering Career Aspiration' was justified in several ways. Firstly, as outlined in earlier chapters, aspirations are framed within this thesis as an age-appropriate indicator of engineering inequity for secondary school-aged learners. As the aim of this process is to create an instrument to distinguish patterns of inequity amongst these learners an aspirational dependent variable is theoretically valid and consistent with the framing of this thesis investigation. Secondly, the choice of this dependant variable is also consistent with the underlying Bourdieuian conceptual framework of capital applied in these instrument items. Bourdieuian capital is a valid perspective on issues of social reproduction, including access to careers and occupational characteristics of social groups. This justifies the choice of a career aspiration dependent variable as a proxy for engineering capital. The use of 'Engineering Career Aspiration' could be criticised, however, as lacking a consideration of educational aspirations for engineering which are also recognised throughout this thesis as valid for the consideration of engineering inequity amongst secondary school-aged learners. This is addressed with the addition of a further item ("Although it is a long way off, which of the following describes your views? - I would like to study engineering at university, at college/sixth form, after GCSE/National 5s but not A-Level/Highers, I do not want to study any engineering after GCSE/National 5s, None of the above or I don't know") to this DV to represent educational aspiration given the theoretical importance of this for secondary school-aged participants. This addition was validated with a further Cronbach's analysis of the DV items (N=865, Alpha, based on standardised items = 0.875). Participant scores on this DV measure (ranging from -13 to 15) were divided into low (scale: -13 to -4:, N=342), medium (scale: -3 to 5, N=476), and high (scale: 6 to 15, N=103) thirds on the DV scale. The logistic regression analysis compared two groups – given the low number of 'high' category participants the 'low' group was compared with the combined 'medium' and 'high' groups on this DV scale. In this way the LR analysis could examine those who had lower or higher levels of capital to determine what forms of capital distinguish these groups. Statistical test assumptions were met supporting the use of binary logistic regression analysis (see Appendix F).

This binary logistic regression analysis was conducted on data from 648 participants comparing groups of participants with 'lower' (N=295) and 'higher' (N=353) engineering aspiration scores. Statistical assumptions were tested and confirmed the linearity of the relationship between IVs and DV logit (Box-Tidwell test), a lack of significant multicollinearity (collinearity VIF <5) and a lack of influential outliers supporting the adoption of this procedure (casewise diagnostics). The regression analysis was statistically significant ($X^2(41) = 400.798$, $p<0.001$) and revealed that 11 items significantly predicted engineering aspiration, outlined in Table 6.13 below. The model explained 61.7% of variance within engineering aspiration score data (Nagelkerke R^2) with an overall accuracy of prediction of 81.3% (the accuracy identifying those with lower scores was 79.7%, and the accuracy identifying those with higher scores was 82.7%) (see Appendix F for statistical outputs).

Table 6.13: Significant predictor items of higher or lower engineering aspiration scores based on Logistic Regression analysis.

Item	**Response Scale**	**Positive or Negative Classification Direction (ExpB)**
I have learnt a lot about engineering from museums	-2 to 2 five-point Likert scale	Positive (1.508)
I know how to design and make things	-2 to 2 five-point Likert scale	Positive (1.360)
I know quite a lot about engineering	-2 to 2 five-point Likert scale	Positive (1.606)
I would be confident talking about engineering in lessons	-2 to 2 five-point Likert scale	Positive (1.405)
An engineering qualification can help you get many different types of job	-2 to 2 five-point Likert scale	Positive (1.657)
When you are not in school, how often do you talk about engineering with other people?	0 to 4 five-point Likert scale	Positive (1.439)
How often do you do the following things outside of school: Read books or magazines about engineering?	0 to 4 five-point Likert scale	Positive (1.691)
How often do you do the following things outside of school: Go online to gind out about engineering, e.g. YouTube, engineering websites, play engineering games?	0 to 4 five-point Likert scale	Positive (1.508)

How often do you do the following things when you are not in school: Do DIY, or help fix things around the home?	0 to 4 five-point Likert scale	Positive (1.316)
How often do you do the following things when you are not in school: Do crafts, e.g. knitting, woodworking?	0 to 4 five-point Likert scale (Reverse code)	Negative (0.731)
How often do you do the following things when you are in school: Take an engineering-related school trip?	0 to 4 five-point Likert scale (Reverse code)	Negative (0.585)

These items were collated to form an engineering capital instrument. Scores on these items were tallied, with two items reverse coded, to produce a score from -10 to 34. This was transformed to lie on a scale from 0-105[4] to align with the science capital and Archer-style engineering capital instruments.

This instrument represents the final product of the engineering capital instrument development process. Starting with the large theoretical model of engineering capital the outlined process of statistical analysis facilitated the refinement of a concise and focused empirical tool capable of measuring the engineering capital of participants. The items included within this instrument are those that are most influential in distinguishing young learners with lesser or greater engineering capital (as conceived of in this thesis in relation to engineering aspirations). With only 11 items it is possible to efficiently generate a representation of the engineering capital possessed by young learners. This is a unique tool developed through a robust statistical methodology that can be applied within real world contexts to develop a greater understanding of engineering inequities. The objectives of this thesis identify the need to develop a richer and solution-orientated understanding of engineering inequities in the UK. This instrument can be widely and efficiently applied to better understand how young learners are supported to become future engineers. In this way the engineering capital instrument represents a key output of this thesis.

Conclusions

Following the formation of the engineering capital theoretical model in Chapter Six it was next necessary to develop an empirical instrument capable of examining engineering capital within real-world contexts.

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[4] This transformation was calculated with the following equation: 2.38636(SCORE)+23.8636.

The creation of this instrument is consistent with the objectives of this thesis in developing greater understanding of engineering inequity so as to address challenges facing the UK engineering domain. In the current chapter a process of questionnaire development, data collection and statistical refinement transformed a large questionnaire empirically measuring many forms of capital to a concise 11-item engineering capital instrument. This instrument represents the first domain-specific instrument of Bourdieuian capital for the engineering domain within current literature. Drawing on data from over 900 young learners this instrument is designed to identify the deeper underlying capital distinctions relevant to engineering inequities. With this novel development it is possible to apply the rich theoretical perspective of engineering capital to the population of young learners in the UK to better understand who are supported with the resources to become engineers. In the next chapter this instrument will be tested to confirm its validity and then applied to the thesis dataset to explore the insights on engineering inequity offered by the novel lens of engineering capital.

CHAPTER SEVEN: VALIDATING AND EXPLORING ENGINEERING CAPITAL

Introduction

In previous chapters the first three stages of an instrument development process were completed to form a conceptual framework, theoretical model and empirical instrument of engineering capital. In the current chapter the fourth and final stage of this development process is undertaken to confirm the validity and utility of the developed engineering capital instrument. The ability of the engineering capital lens to meet the objective of this thesis and support greater understanding of engineering inequities in the United Kingdom is theoretically and empirically investigated. First, three hypotheses will be outlined to structure an examination of validity. Next, empirical analyses will test these hypotheses to confirm that engineering capital is: related to patterns of engineering inequity, aligns with current understandings of such inequities, and is sufficiently powerful to support predictions of engineering educational and career aspiration. Finally, having investigated these hypotheses the value of engineering capital as a lens on engineering inequity will be explored within the thesis dataset.

Validating the Engineering Capital Instrument

Having formed an instrument to measure engineering capital it is next possible to enact the final stage of the adopted instrument development process and apply the instrument to confirm its validity and utility. Benson and Clark (1982) and Streiner and Kottner (2014) acknowledge that such confirmations of instrument efficacy are ongoing, requiring repeated use and testing. Although sustained application is not possible within the confines of this thesis, it is possible to begin this process and explore engineering inequities amongst secondary school learners using the engineering capital instrument.

Any judgement of validity or efficacy must stem from the intended objective for which engineering capital was designed. Within this thesis the engineering capital model and instrument have been developed to provide a more sophisticated and insightful perspective on engineering inequities within the UK context with the intention of enabling intervention to support greater skills supply and social justice within the engineering domain. This objective can be deconstructed to form three hypotheses to test and confirm the validity of engineering capital.

First, it must be confirmed that engineering capital is related to inequities within the engineering domain. Whilst intended to access forms of capital that are theoretically relevant to engineering inequities it is necessary to empirically confirm that the instrument resulting from this theoretical model does relate to such inequities in the UK context. For young UK learners, it is expected that engineering capital is positively associated with greater engineering educational and career aspirations as an age-appropriate indicator of engineering trajectory and inequity.

Hypothesis One: **'**Engineering capital scores will be positively associated with greater educational and career aspirations for engineering'.

Second, it must be confirmed that measurements taken with the engineering capital instrument are consistent with current understandings of engineering inequity. Contemporary framings of engineering inequity in the UK can be criticised as overly descriptive and passive, acting simplistically as a key performance indicator of progress to equity: for example, as of 2021 16.5% of those in UK engineering roles are women (EngineeringUK, 2022b). These framings of inequity arguably provide little insight into the process through which inequities are formed and sustained. However, despite this criticism these framings of engineering inequity can be used as a benchmark to confirm the 'concurrent validity' of engineering capital: the alignment of novel measurements to pre-existing findings (Stain & Bjornestag, 2020). The engineering capital of groups based on gender or social class can be compared to test the consistency between the distribution of engineering capital and acknowledged group inequities within the engineering domain. Examination of differences between further groups, based on theoretically recognised but rarely empirically examined characteristics such as academic ability or national context, may provide novel insights into engineering inequity within the UK. These tests will mirror the critique of science capital in Chapter Four and can confirm the concurrent validity of engineering capital as a tool to understand engineering inequities.

Hypothesis Two: **'**Engineering capital scores will align with previously acknowledged patterns of inequity within the UK engineering domain'.

Finally, it must be confirmed that the association between engineering capital and engineering inequity is strong enough to warrant application of the model and instrument to address these inequities in the UK context. Even very small effects within a sample can be found to be statistically significant if that sample is sufficiently large (Faber & Fonseca, 2014). To confirm that the findings of the first two hypotheses relate to a strong and practically useful perspective on engineering inequity, the engineering capital instrument will be further tested to confirm its ‘predictive validity’ (Schuler, 2001). These tests will examine the degree to which engineering capital can be used to accurately predict aspirations in engineering inequity amongst the collected sample. If the engineering capital instrument cannot be used to predict whether participants wish to study or work in engineering roles, then the relevance or practical value of this novel tool must be questioned.

Hypothesis Three: ‘Engineering capital scores will be capable of predicting aspirations for engineering education or careers amongst young learners’.

The three hypotheses will, collectively, determine the degree to which engineering capital can be acknowledged as a valid and effective instrument for the understanding and exploration of engineering inequity in the UK. If these hypotheses are confirmed then the engineering capital model and instrument can be judged as valid and can next be confidently applied to explore the insights and value of engineering capital as a lens on UK engineering inequities. The failure to confirm any of these three hypotheses would question the validity of the engineering capital instrument and identify the need for further investigation and development to effectively examine engineering inequity in the UK.

Chapter Research Methods

Methodology

The aim of the investigation of this chapter was to confirm that engineering capital applies to engineering inequity as intended. A quantitative strategy was adopted due to the quantitative nature of the developed instrument. The three hypotheses were designed to test the fundamental dynamic between the instrument and engineering inequity to confirm its relevance to inequity, past findings, and understanding of inequity amongst the target audience of young learners. This draws on the conceptual framework outlined in Chapter Five and the philosophical positioning outlined in the Methodology chapter.

Participants

Data was collected from 921 secondary school-aged (11 to 16 years old) learners from ten schools in England and Scotland. As noted in the Methodology chapter, a single point of data collection was adopted for this thesis research project due to the demands of the Covid-19 pandemic. The sample of 921 learners examined in this chapter is the same sample examined throughout the thesis. See Methodology chapter for full outline of sample characteristics and rationale for the selected participant population.

Instruments

A number of instruments and items were drawn upon from the thesis questionnaire to examine the validity of the engineering capital instrument. These are outlined below.

Engineering capital instrument: The 11-item engineering capital instrument created and outlined in Chapter Six was adopted to calculate the engineering capital scores of participants. Item responses were tallied to form a single engineering capital score for each participant on a scale of 0-105. Engineering capital scores were used to code participants as possessing low (0-34), medium (35-69) or high (70-105) levels of engineering capital. This division of the response scale into thirds was adopted from Archer et al.'s (2015) science capital development process and the definition of science capital groups within the science capital literature. A direct adoption of this approach would support comparison with science capital scores and was justified as an efficient and objective approach to distinguishing those with greater or less engineering capital. See Chapter Six for further details on this instrument.

Engineering inequity: Three items were used to establish the engineering educational and career inequities of participants. As outlined in the Methodology chapter, aspirations are an age-appropriate indicator of engineering inequity for secondary school-aged learners. One item examined educational aspiration ("Although it is a long way off, which of the following describes your views: I would like to study engineering at university, at college/sixth form, after GCSE/National 5s but not A-Level/Highers, I do not want to study any engineering after GCSE/National 5s, None of the above or I don't know"). To assess engineering career aspiration participant general interest in engineering careers was established ("Do you think you might like to work in an engineering-related job in the future? Yes, No") alongside a further question concerning a future in the role of 'engineer' specifically ("How much do you agree with the following statements: I want to become an engineer: strongly disagree, disagree, neither agree nor disagree, agree, strongly agree").

Sample characteristics: Participants were asked to report their current year of schooling to determine their progression through the education system and age ("What year group are you in?"). Participants were asked to provide a gender identity to facilitate an examination of capitals for engineering by gender group ("Are you a girl or boy? Girl, Boy, Other Identity"). Respondents were also asked to provide their ethnic identity to examine potential distinctions in capital amongst differing ethnic groups in response to recognised inequities in ethnic representation in UK engineering (What of the following best describes your ethnic origin?"). Respondents were also asked to name their school allowing an examination of geographical distribution of the sample ("What is the name of your school?"). Social class of participants was accessed through two measures drawing on a measure of cultural capital and positioning with the

Income Deprivation Affecting Children Index (IDACI) sub-index of the Indices of Multiple Deprivation (IMD) measure (see Methodology chapter for further details). It was not possible to examine the secondary school-aged participants in relation to academic ability for engineering as this is not a curricular subject for most learners in the UK. Instead, academic ability in the science and mathematics domains were examined through questioning which academic set the participant belonged to for science and mathematics classes ("Which of the following statement below is true for you now? I am in one of the top sets, middle sets, bottom sets, there are not sets in my school.").

Relationship with engineering: Items were also included to explore the wider relationship between the participant and the domain of engineering. These characteristics could later be examined in relation to inequities to better understand how individuals with greater or lesser engineering capital differed – should the three hypotheses be confirmed. These items are outlined in Table 7.01 below.

Table 7.01: Items adopted to explore the relationship between participants and the engineering domain.

Purpose	Item	Response Scale
Examination of social contact with professional engineers	Do you know anyone (family, friends, or community) who works as an engineer or in a job that uses engineering?	0 to 1 binary yes/no response
Recognition of engineering amongst school experiences	Have you come across engineering in your education so far, and if so where?	In a science class, in a design and technology class, in a maths class, in an engineering class, I have not come across engineering in my education
Participation in curricular-mapped experiences	Have you participated in any engineering education programmes or competition? – Secondary Engineer, Science Fairs, Ultimate STEM Challenge, or other challenges?	0 to 1 binary yes/no response
Engineering self-belief	People who are like me work in engineering	-2 to 2 five-point Likert scale
Perception of the openness of engineering trajectories	Anyone can become an engineer	-2 to 2 five-point Likert scale
Perceived utility of engineering	It is useful to know about engineering	-2 to 2 five-point Likert scale
Participant interest in engineering learning	I think learning about engineering is boring	-2 to 2 five-point Likert scale – reverse coded

Perceived value of engineering to participant future	It would be good for my future to know about engineering	-2 to 2 five-point Likert scale
Expectation of personal success in engineering	I believe I could be successful at engineering in the future’	-2 to 2 five-point Likert scale

The complete questionnaire is available in Appendix C.

Procedure

The questionnaire instrument was designed, developed, and applied for data collection as outlined in the Methodology chapter. Following data processing and cleaning the thesis dataset was examined to analyse the three hypotheses outlined in this chapter.

For hypothesis one, this analysis involved the adoption of mean comparison testing to determine the relationship between engineering capital and engineering aspirations. Independent samples t-tests and one-way ANOVA analyses were used to compare the engineering capital scores of those who do or do not report aspirations for engineering education or careers. The adoption of these tests was confirmed as appropriate through testing of statistical assumptions. Such means testing is acknowledged as appropriate for the comparison of different groups on an empirical scale (Ho, 2013).

For hypothesis two, descriptive statistics and further mean comparison testing was adopted to examine the distribution of engineering capital between groups. Frequency analysis, independent samples t-tests and one-way ANOVA analyses were deployed to examine the distribution of engineering capital between groups that had previously been acknowledged as inequitably represented within UK engineering including: gender, social class, national context (England and Scotland) and academic ability sets for mathematics and science. The adoption of these tests was also confirmed as appropriate through testing of statistical assumptions; these tests were supported as appropriate for examinations of group differences (Ho, 2013).

For hypothesis three, binary logistic regression analyses were adopted to examine the predictive power of the engineering capital model for understanding engineering educational and career inequities. This statistical test can determine the ability of models to correctly classify individuals as belonging to certain groups – in this case, the ability of engineering capital to correctly classify individuals as aspiring to engineering trajectories or not. The ability to clearly reduce aspirations for engineering to a binary yes/no response supported the use of binary logistic regression over other regression approaches (Ho, 2013). The adoption of these tests was confirmed as appropriate through validation of test assumptions.

Following the testing of these hypotheses, an assessment of the engineering capital model and its implications was outlined in relation to past literature. Further descriptive statistics were adopted within this examination to articulate the differences between those with lesser or greater engineering capital.

Results and Discussion

Three hypotheses were statistically tested to confirm the validity of the engineering capital instrument as a lens on engineering inequity.

Hypothesis One: 'Engineering capital scores will be positively associated with greater educational and career aspirations for engineering'.

Educational Aspiration for Engineering

Participants were asked if they wished to study engineering in the future with positive answers coded as 'Yes' and those unsure or negative coded as a 'No' group. A Welch's independent samples t-test revealed significant differences in engineering capital score ($t(348.950) = 17.301$, $p<0.001$, $d=1.379$) with those aspiring to engineering education scoring higher on engineering capital ($N=228$, $M=60.95$, $SD=13.55$) than those who did not ($N=659$, $M=43.58$, $SD=11.60$) (see Appendix G for statistical outputs). The Cohen's d effect size statistic ($d=1.379$) indicated a very strong effect demonstrating that engineering capital is a deeply significant delineating characteristic between those who do or do not aspire to engineering education. These results are outlined in Figure 7.01 below.

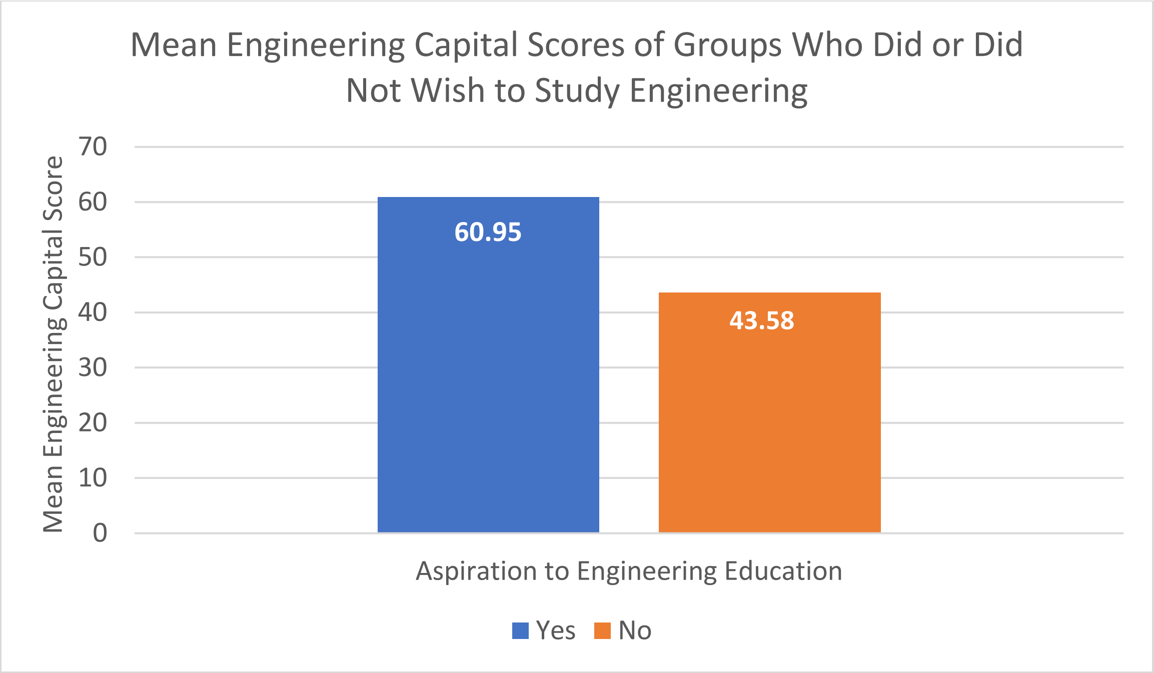

Figure 7.01: A bar graph of the mean engineering capital score of groups who do or do not wish to study engineering in some form following secondary education.

This can be further examined beyond binary responses by comparing the engineering capital of those who aspire to differing pathways for engineering education such as academic study at further education, other study after secondary education such as vocational training, or higher education for engineering. The underlying presumption of engineering capital – that those who possess greater engineering capital are better supported for engineering trajectories – would imply that those who wish to proceed into higher levels of education will possess greater engineering capital. A further one-way Welch's ANOVA was adopted to compare the engineering capital scores of those who aspired to engineering education (No desire to study engineering, unsure, further education (other/vocational), further education (college/sixth form), higher education (university)). This test revealed a significant relationship between engineering capital and the level of engineering education aspired to ($F(4,211.885) = 88.236$, $p<0.001$, $ETA^2=0.32$) with those wishing to study engineering at higher levels possessing significantly greater levels of engineering capital (see Appendix G for statistical outputs). The results of this analysis are outlined in Figure 7.02 below.

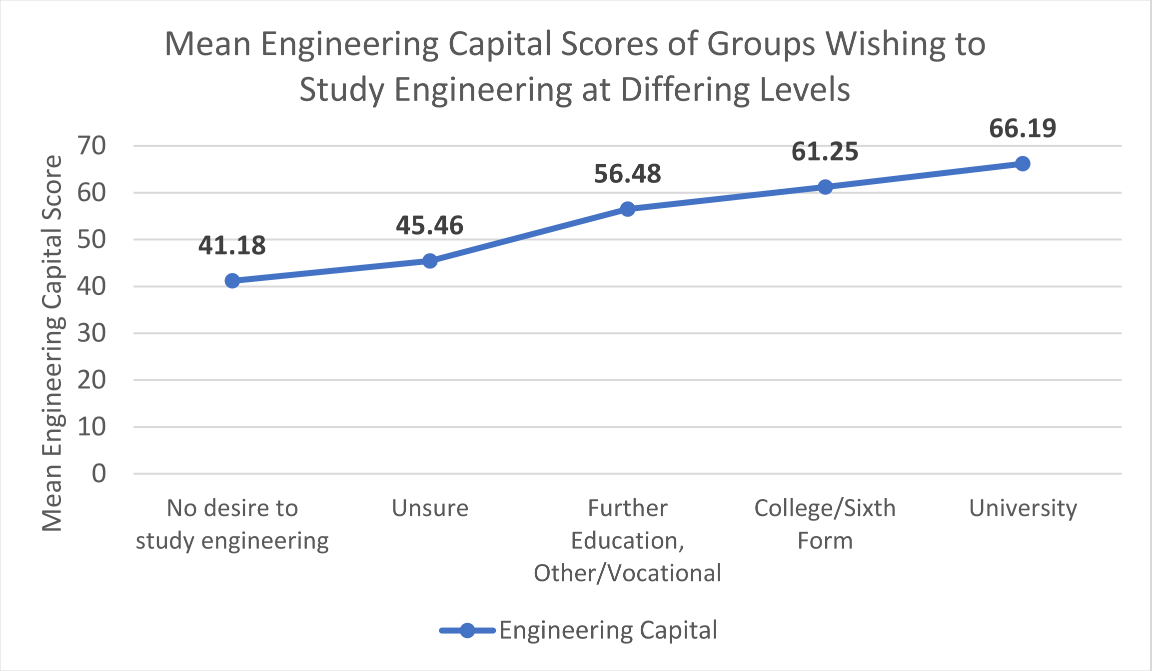

Figure 7.02: A line graph to show the mean engineering capital score of groups who do or do not wish to study engineering: no, unsure, in academic further education, in other further education, in higher education.

However, post-hoc testing questioned how well engineering capital could distinguish those aspiring to differing educational pathways. Engineering capital scores significantly differed between those who did or did not wish to study engineering, and between those who wished to study non-academic routes in further education and those who wished to study engineering at university. A linear positive relationship is noted, but post-hoc analyses suggest that those who wish to study engineering on academic routes (college/sixth form and university) are difficult to delineate. This is logical, however, as those studying on academic routes in college may also wish to later study at university. Further investigation with a larger dataset is warranted to examine this dynamic in greater detail including the differences in engineering capital of those wishing to study vocational or academic routes in college/sixth form settings.

The ETA^2 effect size of this analysis (ETA^2=0.32) indicates a very large effect (an ETA^2 score of 0.14 or higher is considered to be large) further demonstrating the strength of the relationship between engineering capital and educational trajectories for engineering (Richardson, 2011). It may not be surprising that the engineering capital instrument is so effective in this regard given that educational aspirations were included within the formative logistic regression used to create the instrument (see Chapter Six). Regardless, however, this effect size does confirm that this instrument is successful at distinguishing those who do or do not wish to study engineering in the future demonstrating the sensitivity of engineering capital to inequities within engineering and highlighting its value as an empirical indicator of future engineers.

Career Aspiration for Engineering

A Welch's independent samples t-test was adopted to examine the relationship between engineering capital and desire to work in an engineering-related role in the future ("Do you think you might like to work in an engineering-related job in the future?"). The t-test revealed significant differences (t(541.201) = 20.937, p<0.001, d=1.515) in engineering capital score between those who did (N=316, M=59.54, SD=13.15) and did not (N=576, M=41.51, SD=10.58) wish to work in an engineering-related role (see Appendix G for statistical outputs).

A second Welch's independent samples t-test was adopted to examine the relationship between engineering capital and desire to become an engineer specifically ("I want to become an engineer"). The t-test also revealed significant differences (t(152.400) = 16.624, p<0.001, d=1.776), with those wishing to become an engineer (N=119, M=64.80, SD=13.76) possessing greater engineering capital than those who did not (N=581, M=42.42, SD=11.32) (see Appendix G for statistical outputs).

The results of these two tests are outlined in Figure 7.03 below.

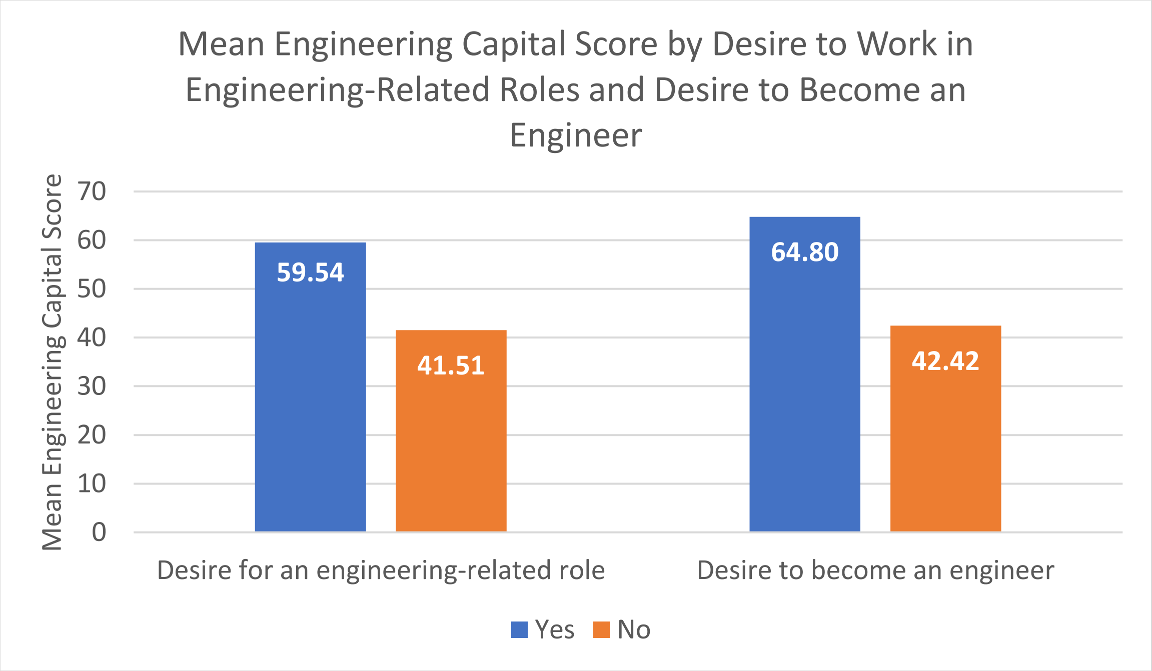

Figure 7.03: A bar graph to show the mean engineering capital score of groups who do or do not wish to work in an engineering-related role or to become an engineer.

The Cohen's d effect sizes of these findings (desire for an engineering-related role: d=1.515, desire to become an engineer: d=1.776) demonstrate engineering capital is a very relevant indicator distinguishing those who do or do not wish to work in engineering roles. This highlights the importance of these forms of resource and validate the use of engineering capital as a lens on inequity.

Hypothesis One Discussion

Educational and career inequities are fundamental, well documented and well commented on aspects of the engineering inequities present within the UK. Both the study of engineering and the uptake of engineering employment are acknowledged to be inequitable with patterned access, participation, representation and success noted for UK engineering study and careers (EngineeringUK, 2018; EngineeringUK, 2020). As an empirical instrument designed to understand engineering inequities, the engineering capital model must, therefore, be responsive to such educational and career inequities. This necessitated the first hypothesis of this validation of engineering capital: 'Engineering capital scores will be positively associated with greater educational and career aspirations for engineering.'

The findings outlined above confirm this hypothesis, validating that the engineering capital instrument is responsive to educational and career inequities in engineering. Those that wish to study (M=60.95) or work (M=59.54) in the engineering domain possess greater engineering capital than those who do not wish to study (M=43.58) or work (M=41.51) in engineering roles. The Cohen's d effect sizes of these comparisons identified very strong effects demonstrating that engineering capital scores strongly differentiate those who do or do not aspire to future engineering trajectories. The success with which engineering capital can distinguish these groups speaks to the validity, sensitivity and utility of a capital-based perspective on engineering inequity and would confirm the underlying presumption that those with greater capital are better supported for engineering trajectories. As a result, we might consider engineering capital as a valid, valuable and relevant theoretical tool and empirical measurement instrument to understand and address inequities within the UK context.

Hypothesis Two: 'Engineering capital scores will align with previously acknowledged patterned inequities within the UK engineering domain'.

It was next possible to explore the distribution of engineering capital to confirm that engineering capital aligns as expected with understood patterns of inequity. To test this, the engineering capital scores of groups previously acknowledged as inequitably represented within engineering were compared, including gender and social class group differences (EngineeringUK, 2018a; EngineeringUK, 2018b). Further theoretically valid but infrequently measured group distinctions were also explored, including national context within the UK and school academic set as a proxy for academic ability (Chapman & Vivian, 2017; Marginson et al., 2013; Wai et al., 2010; Wang et al., 2017). For engineering capital to be validated as a useful and valid lens on engineering inequity, the distribution of engineering capital must align to these acknowledged patterns of representation within engineering.

Gender Differences in Engineering Capital

Gender differences are perhaps the most commonly acknowledged inequity within the engineering domain. As of 2021, only 16.5% of UK engineering roles are held by women (EngineeringUK, 2022b) and only 20.2% of university undergraduate engineering and technology enrolments in 2020/21 were by women (HESA, 2022). This is noted within the thesis dataset where only 16.5% of girls would consider studying engineering in some form in the future, compared to 40% of boys. The engineering capital instrument must be responsive to such entrenched patterns if it is to be acknowledged as a valid lens on engineering inequity. A Welch’s independent samples t-test was utilised to examine the differences in engineering capital score by gender group and found a statistically significant difference in scores ($t(706.293) = 7.816$, $p<0.001$, $d=0.536$) with boys possessing greater levels of engineering capital ($N=388$, $M=52.07$, $SD=15.98$) than girls ($N=505$, $M=44.43$, $SD=12.28$) (see Appendix G for statistical outputs). The Cohen’s d effect size ($d=0.536$) established a medium strength effect of gender group on engineering capital score. These findings align to previously acknowledged engineering inequities supporting that engineering capital is a valid lens on inequity within the UK context. The results of this analysis are outlined in Figure 7.04 below.

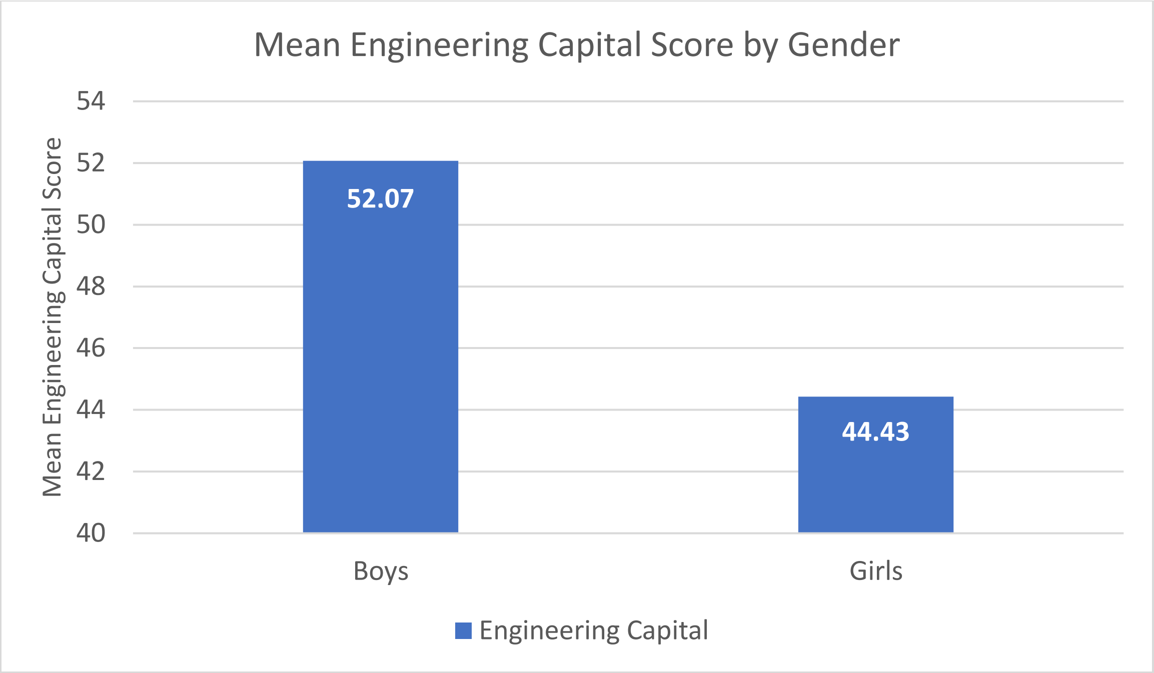

Figure 7.04: A bar graph to show the mean engineering capital score of gender groups: boys and girls.

<u>Social Class Differences in Engineering Capital</u>

Engineering inequities within the UK context are also acknowledged to be patterned by social class in such a way that those from more privileged socioeconomic backgrounds are overrepresented within engineering roles (EngineeringUK, 2018b). The measurement of engineering capital must therefore detect such social class differences in its measurements to be considered valid. To test this a one-way ANOVA examined the differences in engineering capital scores of class groups defined in terms of cultural capital and found significant differences ($F(4,916) = 8.167$, $p<0.001$, $ETA^2=0.034$) with those of higher social group possessing significantly greater engineering capital. Post-hoc testing revealed significant differences between almost all groups – though the limited representation in the 'very low' category (N=10) skewed accuracy of findings for this group (see Appendix G for statistical outputs). The ETA^2 effect size ($ETA^2=0.034$) of this analysis indicates a small-medium effect size of social class differences on engineering capital score. This effect size demonstrates that social class (measured with the sociocultural lens of cultural capital) does impact engineering inequities as expected. The strength of this effect can be deemed as reasonably accurate given the acknowledged skew to privileged groups is moderate – this effect is, as expected, less than that of gender differences. The linearity of this relationship between social class and engineering capital is consistent with the underlying premise of greater capital relating to greater advantage. These results support the validity of engineering capital as a lens on engineering inequity in relation to social class. The results of this analysis demonstrating its linearity is outlined in Figure 7.05 below.

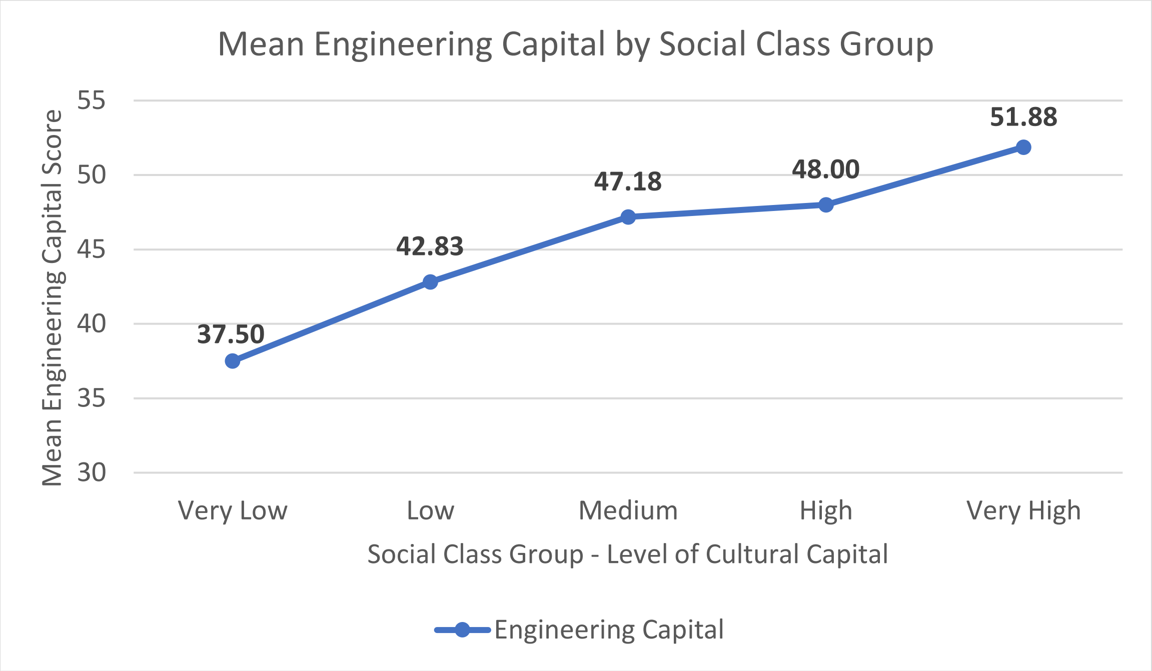

Figure 7.05: A line graph to show the mean engineering capital score of social class groups defined in relation to cultural capital.

As noted in the chapter research methods section, it is also possible to examine social class in strictly economic terms using the IDACI instrument, though such economic framings of social class are noted to be of lesser sensitivity in past literature. A one-way ANOVA analysis examined the relationship between engineering capital and social class groups based on IDACI quintiles but found no significant differences (F(4,601) = 1.182, p=0.318, ETA^2=0.008) (see Appendix G for statistical outputs). This suggests that economic deprivation, as framed within the IDACI measure, is not related to engineering capital. Given the limitations of this approach to operationalising social class and the strong positive results in the first, sociocultural framing of social class, we might infer that the economic approach used here with IDACI quintiles is not effective. Past uses of this approach in Chapter Four would offer support to this assessment.

Science/Mathematics Academic School Set Differences in Engineering Capital

Academic ability in science or mathematics is a less commonly considered characteristic of engineering inequity in the UK despite the institutionally enforced relationship between performance in these domains and entry requirements to higher levels of engineering study. Within this educational structure it would be expected that those with the 'higher' academic abilities (as defined by the standards of the institution controlling these groupings) would possess greater engineering capital. This was tested with two one-way ANOVA analyses.

The first ANOVA found statistically significant differences (F(3,893) = 5.043, p=0.002, ETA^2=0.017) in the engineering capital of school science sets. Post-hoc testing revealed significant differences between the 'middle' and 'higher' sets, and the 'middle' and 'lower' sets but no difference between the 'higher' and 'lower' sets (see Appendix G for statistical outputs). The ETA^2 effect size (ETA^2= 0.017) indicates a small effect of academic set for science on engineering capital scores. These results are outlined in Figure 7.06 below.

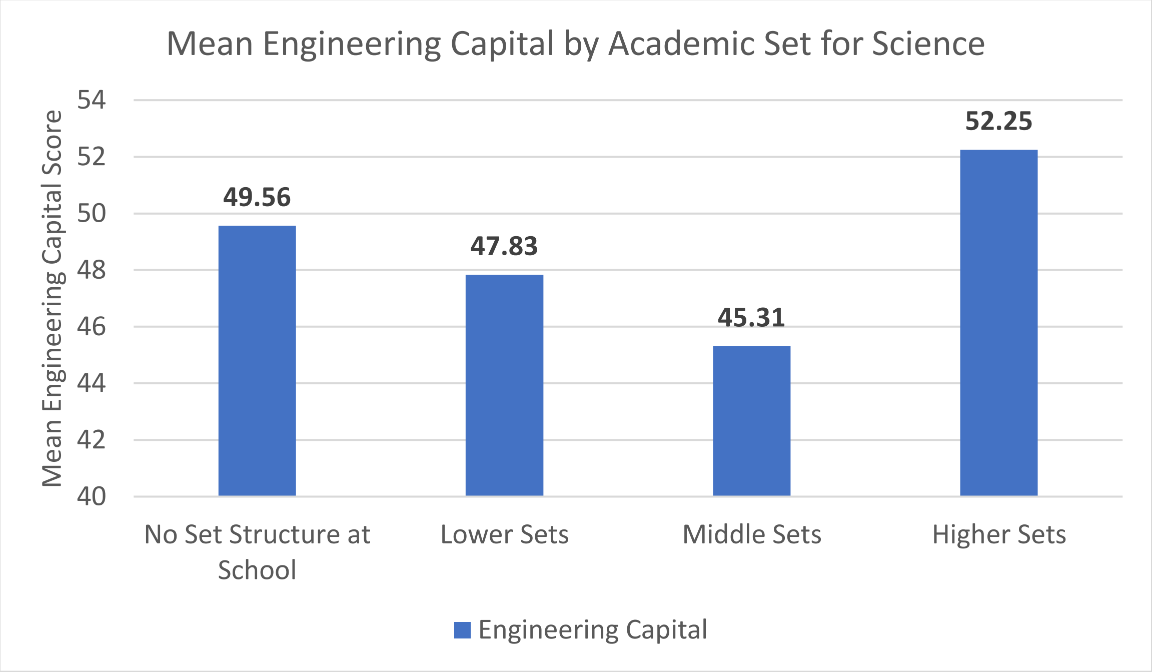

Figure 7.06: Bar graph to show mean engineering capital by academic set for science.

A second one-way ANOVA found statistically significant differences (F(3,897) = 4.272, p=0.005, ETA^2=0.014) in engineering capital of differing school mathematics sets. Post-hoc testing revealed significant differences between the 'middle' and 'higher sets, and the 'middle' and 'lower sets but no difference between the 'higher' and 'lower sets (see Appendix G for statistical outputs). The ETA^2 statistic (ETA^2=0.014) indicates a small effect size. These findings are generally consistent with the assessment of science academic sets. These results are outlined in Figure 7.07 below.

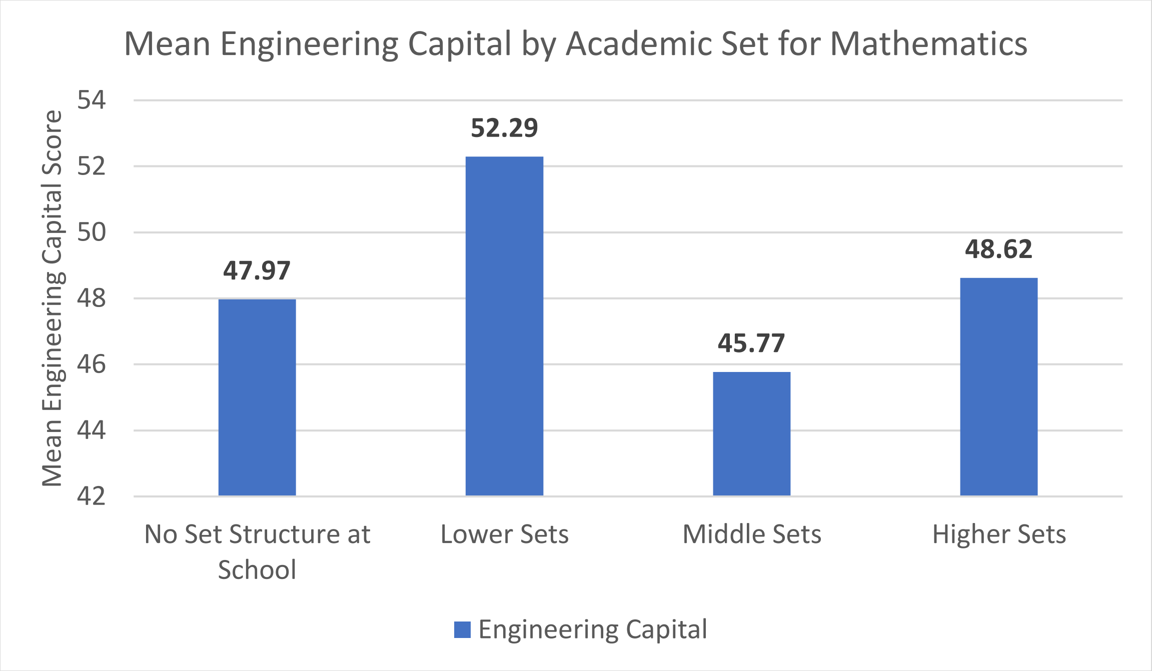

Figure 7.07: Bar graph to show mean engineering capital by academic set for mathematics.

It must be noted that the sample size for the 'lower sets' group was disproportionately small (Science: N=48, 5.2% of total sample; Maths: N=48, 5.3% of total sample) which may compromise the accuracy of measurement for this group. However, this concern is diminished with examination of the remaining groups: it would be expected that the 'no set structure at school' group mean score would equal the average of lower, middle, and higher set means given the natural mix of students within a school without a set structure to academic classes. The mean score of lower, middle and higher sets for science is similar to the no set structure at school for science (mean difference= 1.10), as is the case for mathematics sets (mean difference= 0.98) suggesting that the lower sets class may be accurate regardless of the limited sampling – but further data collection is warranted.

These findings outline a relationship within the engineering capital of academic sets but departs from the expectation of a linear relationship with notedly higher engineering capital amongst 'lower sets' groups. These findings would still support the nuance with which engineering capital can examine engineering inequities amongst differing groups but challenges the notion that those 'high ability' individuals must be the only ones to possess high levels of engineering capital. The novelty of these findings is discussed later in this chapter.

National Context Differences in Engineering Capital

Whilst often generalised to a UK-wide perspective it must be acknowledged that the UK contains four devolved administrations resulting in distinct institutional practices and policies which may influence engineering inequities. This is particularly salient in educational research given distinctions in educational institutions between the four nations. However, underlying these institutional differences are remarkably similar societies and cultural contexts suggesting a homogeneity that may limit the degree to which engineering capital differs between these contexts given the sociocultural underpinning of engineering capital. Participants within this thesis were recruited from both Scotland (N=89) and England (N=832) allowing a comparison of engineering capital within these populations

An independent samples t-test was used to examine the difference in engineering capital scores by national context, comparing England and Scotland, and found no significant differences between the two nations (t(919) = 0.155, p=0.877, d=0.017) with no differences between the scores of England (M=47.70, SD=14.41) and Scotland (M=47.45, SD=14.61) (see Appendix G for statistical outputs). This suggests that the two populations possess similar volumes of engineering capital and that the two devolved approaches to engineering education may not produce a notable difference in engineering capital – but this would need to be examined with a larger and representative sample to confirm. This result could also be interpreted as supportive of the validity of engineering capital instrument given that engineering inequities are noted in both national contexts (APPG on Diversity and Inclusion in STEM, 2021; Scottish Government, 2020).

Hypothesis Two Discussion

Engineering inequities within the UK context are long acknowledged with distinct patterns of access, participation, success and representation amongst certain groups leading to an overrepresentation of white males from more privileged socioeconomic backgrounds and underrepresentation of woman, people from non-white ethnicities, and those from less privileged backgrounds (EngineeringUK, 2018a; EngineeringUK, 2018b; EngineeringUK, 2020). In Chapter One such framings of inequity are compared to key performance indicators of the journey to equity but criticised as lacking deeper utility in comprehending the underlying mechanics which shape these patterns. The engineering capital model and instrument is offered as a richer lens on engineering inequities but to be accepted must align with these longstanding patterns of inequity. This test of 'concurrent validity' determines the value of engineering capital in its consistency with past findings which in turn supports the validity of its further insights (Elia & Stratton, 2011). Examinations of gender, social class, academic set and national differences each confirm the concurrent validity of engineering capital and align its insights to past literature.

The engineering capital instrument is sensitive to long-recognised engineering gender inequities finding that, as expected, boys possess greater engineering capital (M=52.07) than girls (M=44.43). This is consistent with a wealth of past literature that demonstrates findings such as a greater interest in engineering roles, self-identification with engineering as a domain and participation with engineering trajectories amongst boys (EngineeringUK, 2018a; Hutchinson & Bentley, 2011). The finding also indicates that even relatively small differences in scores (mean difference 7.64 on a scale from 0 to 105) can represent profound differences in real world settings – such as the significant gendered inequity present within the engineering domain represented by 7.64 points of difference. This speaks to the additive effect of capital and would support the potential impact of interventions that address specific aspects of engineering capital.

The engineering capital instrument also displays concurrent validity with social class inequities for engineering. When social class is measured with the sociocultural lens of cultural capital those of greater social advantage are found to possess greater engineering capital. These findings are also consistent with acknowledged social class inequities within engineering which skew participation to those of greater social advantage (EngineeringUK, 2018b). However, this investigation of social class also finds no significant difference in engineering capital when social class is examined in strictly economic terms through the IDACI index of economic deprivation.

Furthermore, critique of these inconsistent findings would seemingly support the positive association identified with social class and confirm the validity of engineering capital as a lens on social class inequities. First, past literature acknowledges that sociocultural framings of social class, such as the cultural capital perspective utilised in this thesis, are often more sensitive and insightful than strictly economic structures of social class differences (Davis-Keane, 2005; McMaster, 2017). This would support the validity of the sociocultural finding and limit support for the insignificant economic differences identified in the two tests. It is possible that the social class group distinctions in engineering are weak as to only be detectable by the more sensitive sociocultural perspective. The ETA^2 of this analysis ($ETA^2 = 0.034$) would support this as only a small-moderate effect is present suggesting the more sensitive framing of social class is warranted. Second, it must be acknowledged that sociocultural elements of social class, such as parental occupation or participation with cultural contexts, are acknowledged as relevant to engineering inequities. Within one sample of UK engineers, 8.6% of individuals reported an engineering employed or formerly employed parent (Laurison & Friedman, 2016). Participation with STEM cultural contexts such as science museums are acknowledged as mediated through familial influences in an inequitable manner (Godec et al., 2022). These findings thereby demonstrate that sociocultural characteristics of class are relevant to the engineering domain validating the value of the engineering capital model which can detect differences in these forms of social class indicators. Finally, it must be noted that the contents of the engineering capital instrument itself are sociocultural, rather than economic, in nature. The model and instrument contain sociocultural characteristics such as 'engineering literacy' or 'engineering dispositions' but does not contain the factors central to economic framings of inequity such as household income. It must therefore be acknowledged that the instrument of engineering capital is itself inherently better aligned to a sociocultural lens of social class. These points, collectively, speak to the validity of the sociocultural social class findings within this thesis and thereby establish the sensitivity of engineering capital to social class differences. This supports the concurrent validity of engineering capital as a novel lens on engineering inequity. Further examination is warranted, perhaps making use of multiple sophisticated measures of social class and a large quantitative sample to further articulate the nuance in social class differences and the engineering domain.

The confirmation that engineering capital follows the expected patterns of engineering inequity in gender and social class support the concurrent validity of engineering capital as a model and instrument exploring engineering inequity. This support is further built on through examinations of less commonly measured, but theoretically valid, group differences in the engineering domain. The engineering capital of academic sets for science and mathematics, which might be understood as an indicator of how schools view their most 'able' students, are found to be patterned demonstrating inequities within academic ability. A patterned relationship between capital and academic ability or achievement is consistent with the traditional Bourdieuian perspective that positions the education system as an institutional extension of the dominant culture that better serves those possessing greater cultural capital (Bourdieu & Passeron, 1977; Bourdieu, 2002; Nash, 1990). This produces greater ease for those with cultural capital providing an educational advantage. Given this, we might expect that those in higher academic sets for science or mathematics would possess the greatest levels of engineering capital. However, wider literature would also suggest that those in lower academic sets may possess greater engineering capital. Engineering as a domain can be acknowledged as more 'body-orientated' involving key skills and practices such as visualisation and spatial reasoning (Hsi et al., 1997). This thereby represents a more 'embodied cognition' than other more mind-orientated subjects such as science or mathematics (Pleasants and Olson, 2019; Sullivan, 2018). A more embodied domain such as engineering may challenge the convention of the 'able' learner institutionalised through an academic set structure organised around mind-orientated subjects such as science or mathematics. As a result, there is a reasonable expectation that those in lower academic sets for subjects such as science or mathematics may be in possession of greater capital within the engineering domain. The findings within this thesis confirm both expectations. The difference in engineering and science capital scores for those in differing ability sets for mathematics – a subject used in both science and engineering – differ. Where science capital mean scores are largely the same between those in lower (36.42) and middle ability sets (37.07) (mean difference = 0.65), these groups possess differing levels of engineering capital with those in lower sets possessing greater engineering capital (52.29) than those in middle sets (45.77) (mean difference = 6.52). This is visualised in Figure 7.08 below. A similar but weaker pattern of results are found for science academic sets with the mean difference between those in lower and middle sets for engineering capital (mean difference = 2.52) compared to science capital (mean difference = 0.65). These findings further demonstrate the novel insight of engineering capital and the distinction of the engineering domain in comparison to science. This finding suggests that those in lower ability mathematics groups are more readily provisioned with resources that will support their aspirations in engineering than they are with resources in support of science aspirations. The pattern of data highlights yet another distinction between science and engineering in real world contexts and further challenges the notion that a ‘science first’ structure to the education system is compatible with supporting engineering, as discussed in Chapter One. These findings also suggest that mathematics and science may offer distinct value in supporting future engineers. This may inform interventions to combat inequities in the engineering domain: mathematics may offer novel strategies, including curricular designs or pedagogical approaches, to combat inequity and widen participation with engineering. The relationship between capitals for science and engineering and academic ability should be further investigated to explore how the greater embodiment of engineering interacts with the supportive capital possessed by differing cohorts.

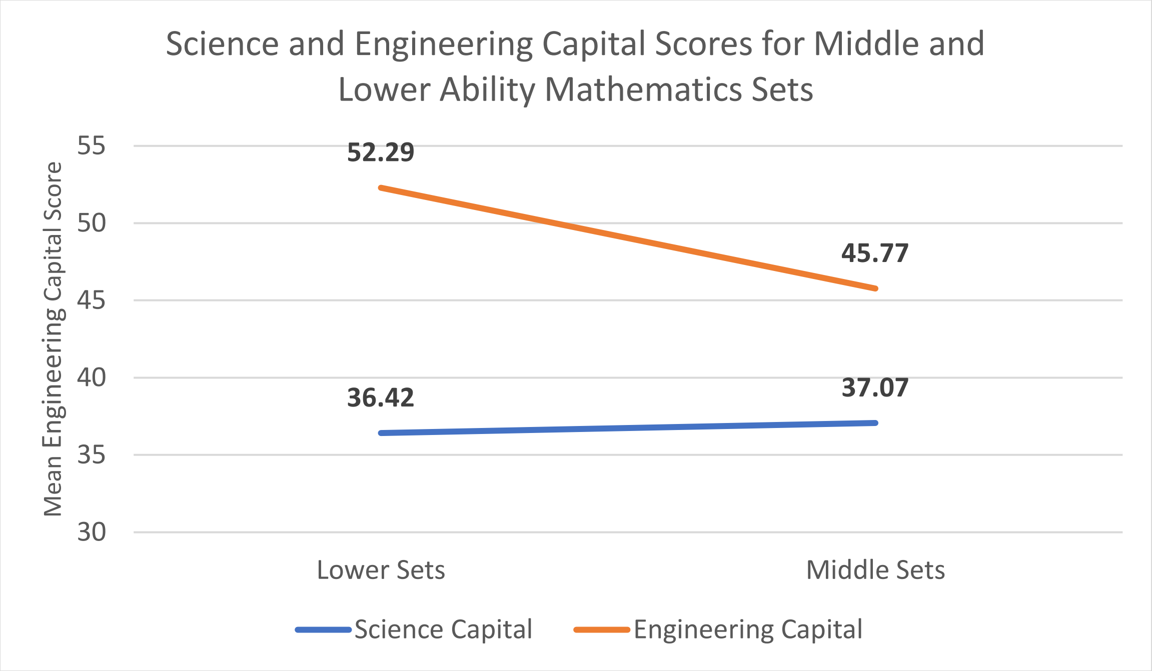

Figure 7.08: Science and engineering capital scores for middle and lower ability mathematics sets.

The confirmation of both literature-led expectations of academic sets and their possession of engineering capital is insightful and a powerful validation of the engineering capital lens on engineering inequity. The confirmation of both literature-led findings supports the validity and sensitivity of the engineering capital instrument but also acknowledges its capacity to support novel knowledge development and synthesis. Given the limited examination of academic set structure and engineering trajectories within past literature these findings demonstrate a meaningful and novel development in the understanding of who is supported to become an engineer within UK educational institutions. This finding has implications for how trajectories towards engineering are structured: the finding that those in lower science and mathematics may possess the resources to support individuals to become engineers is at odds with the institutional pipeline to higher education which frequently requires achievement in mathematics or physics qualifications. In this way, the engineering capital instrument can provide novel insights into not only participation with engineering but also the impact of the institutional structures which shape the engineering population. These insights would align with patterned outcomes from engineering trajectories that allow some to become ‘professional engineers’ through accredited higher education pathways and those ‘engineering technicians’ who train through vocational routes. The engineering capital examination within this thesis suggests that the distinction of these two groups, itself a form of inequity given unequal standards of employment and benefits, may be rooted in how young learners are stratified by schools according to assessments of 'ability'. This further demonstrates the significance of examining secondary school-aged samples despite the general focus on later stages of education within engineering educational research. These novel insights not only demonstrate that the engineering capital model and instrument align to patterns of inequity but highlight its value as a deeply insightful, critical lens on the place, participation, and structure of engineering within UK society.

The concurrent validity of the novel engineering capital instrument to established patterns of engineering inequity confirm the prediction of hypothesis two and support the utility and relevance of engineering capital as a lens on engineering inequities. This supports the value of this novel development in relation to the economic and social justice considerations of engineering access, participation, success representation in the UK context.

Hypothesis Three: 'Engineering capital scores will be capable of predicting aspirations for engineering education or careers amongst young learners'.

Having established engineering capital as relevant to group distinctions for engineering, it is next possible to investigate the relative importance of engineering capital to engineering inequities. As even small effects can appear significant within large samples, it is necessary to test the relative importance of engineering capital to patterns of inequity. Though not designed as a predictive model, the ability of engineering capital to predict educational or career aspirations of young learners is a useful test to gauge the impact of engineering capital on these patterned inequities. This 'predictive validity' can determine the value of engineering capital as a meaningful, succinct lens on the complex and widely shaped patterns of aspiration. If the engineering capital instrument can be used to correctly predict aspirations for engineering, then this would indicate that the engineering capital an individual possesses is deeply influential in determining patterns of aspirational inequity.

To test this binary logistic regression analyses were adopted to examine the degree to which engineering capital scores could accurately classify engineering inequities.

The first binary logistic regression examined the relationship between engineering capital and educational aspirations. A statistically significant regression model was established ($x^2(1) = 271.705$, $p<0.001$) that explained 38.8% of the (Nagelkerke R^2) variance in educational aspiration data. The engineering capital model correctly identified 80.6% of participants as aspiring or not aspiring to engineering educational trajectories – a 91.8% accuracy at identifying those that did not aspire, and a 48.2% accuracy for those that did wish to study engineering (see Appendix G for statistical outputs).

A second binary logistic regression examined the relationship between engineering capital and career aspirations for engineering-related roles. A statistically significant regression model was also established ($x^2(1) = 374.683$, $p<0.001$) that explained 47.1% of the (Nagelkerke R^2) variance in career aspiration data. The engineering capital model correctly identified 80.0% of participants as aspiring or not aspiring to engineering-related careers – an 87.0% accuracy for those that did not aspire, and a 67.4% accuracy for those wishing to work in an engineering-related job (see Appendix G for statistical outputs).

Hypothesis Three Discussion

These regression analyses demonstrate the significant ability of engineering capital to predict engineering aspirations. The instrument can be used to correctly discern the educational aspirations of 80.6% of young learners and can also correctly discern the career aspirations of 80.0% of this group. This confirms the third hypothesis ('Engineering capital scores will be capable of predicting aspirations for engineering education or careers amongst young learners') and thereby indicates that engineering capital is an influential indicator associated with engineering aspirations. This supports the predictive validity of the novel engineering capital model and instrument. It must be noted that those who do aspire to engineering trajectories are more difficult to predict than those who do not – engineering capital can predict 48.2% of those who wish to study engineering and 67.4% of those who wish to work in an engineering-related role. As expected, these predictive accuracies are lower than those for the overall model. This is unsurprising given the complexity and scarcity of aspirations to engineering and the relative abundance of young learners who do not aspire to engineering roles. This results in a greater degree of discernment for those who do aspire to engineering trajectories. However, the high level of accuracy for those who do not wish to study (91.8%) or work (87.0%) in engineering roles is also informative in the pursuit of understanding engineering inequities and developing interventions to address them. The judgement of what constitutes an 'acceptable' predictive power is subjective: a test accuracy of 80% may be unacceptable for a medical diagnostic test but would be very strong for a complex sociological phenomenon. The complexity, nuance and consequence of inaccurate measurement should contribute to a subjective judgement of acceptability.

Subjectively the performance of engineering capital to correctly predict almost half of engineering educational aspirations and more than half of career aspirations can be positively interpreted. With only 11 items the engineering capital instrument is capable of distinguishing a large proportion of participants and their engineering trajectories. This demonstrates that capitals for engineering are influential in relating to, or shaping, patterns of engineering inequity. Engineering capital can be judged as significant in relation to educational and career aspirations given this predictive power. The accuracies with which engineering capital can predict engineering aspirations is an improvement on the predictive power of science capital which can only identify 0.0% of those wishing to study engineering and 0.1% of those wishing to work in engineering roles as outlined in Chapter Four. The engineering capital model, as a first iteration of an engineering-specific model of capital, can be understood to possess significant predictive validity supporting its value and novelty to approaching engineering inequities in the UK context. Future work may improve upon this model and its predictive power.

The Insights of Engineering Capital

The confirmation of these three hypotheses reinforce the validity of engineering capital as a lens on engineering inequities within the UK context. Engineering capital is associated with engineering inequity, follows acknowledged patterns of this inequity and can be utilised with decent predictive power to understand the educational and career aspirations of young learners.

Having confirmed that engineering capital is a valid tool it is next possible to explore the insights offered by this newly developed model and instrument.

The Distribution and Distinctions of Engineering Capital Groups

The degree to which young learners in the UK possess supportive capital for engineering can be examined through distribution analysis to better understand the scarcity of supportive resources for engineering in the UK. Engineering capital scores were used to code participants as possessing low (0-34), medium (35-69) or high (70-105) levels of engineering capital. Frequency of membership in each category provides the distribution of scores for engineering capital within this sample. These scores are outlined in Table 7.02 below.

Table 7.02: Frequency of low, medium, and high engineering capital scores.

Level of Engineering Capital	**N**	**Percentage of Total Sample**
Low	175	19.0%
Medium	656	71.2%
High	90	9.8%

Only a small proportion of young learners possess a ‘high’ level of engineering capital, which suggests that under 10% of this group are strongly provisioned with the social and cultural resources for participation and success in engineering. The frequency of 'medium' scores, totalling 71.2% of this secondary school-aged sample, may appear surprising given the relatively poor presence of engineering within national curricula. However, it is important to note that the engineering capital instrument was intentionally designed to access resources beyond the classroom setting that may be experienced through lived experience given, as introduced in Chapter One, engineering holds a significant historical and contemporary role within the UK culture and society. If the engineering capital model and instrument only included those forms of capital provided through classroom experiences, then the distribution and predictive impact of this instrument would likely differ. The further identification that 20% possess a low level of engineering capital does demonstrate that support for engineering is inequitable and that a large proportion of young people in the UK are poorly supported with resources for engineering.

The classification of individuals into groups based on their supportive engineering capital facilitates a deeper study of those who are more or less supported for participation with engineering trajectories. Engineering capital groups can be compared to not only illuminate who are most supported to become engineers but also to identify further distinctions associated with the possession of engineering capital such as how engineering is conceived of, valued, previously encountered and aligned to learning.

'High Engineering Capital Group'

Those with a 'high' engineering capital scored from 70 to 105 on the 0-105 scale of engineering capital. This group represented only 9.8% of the 921 participant sample and can be understood as those who possess the greatest supply of resources for engineering and thereby are most supported to become engineers. In terms of personal characteristics those with 'high' engineering capital are disproportionately male (76.4% male, compared to a sample average of 43.4%) and more likely to come from more privileged social backgrounds (62.2% come from 'high' or 'very high' cultural capital groups, compared to a sample average of 50.0%).

Those with 'high' engineering capital scores are more likely to have encountered engineering experiences in their life so far. They are:

- More likely to know an engineer (70.5%, compared to a sample average of 49.5%),
- More likely to have experienced an engineering-related educational programme (22.2% compared to the sample average of 10.9%) such as a Big Bang Science Fair or Primary Engineer programme,

- And more readily recognise engineering within their curricular educational experiences to date (86.7%, compared to an average of 68.4%).

As expected, those with ‘high’ engineering capital scores aspire to engineering roles more frequently. They are:

- More likely to want to study engineering (77.5%, compared to the average 25.7%),
- More likely to desire to work in engineering-related roles (91.0%, compared to the average 35.4%).

The ‘high’ engineering capital young learners are also more positive about the openness of engineering trajectories. They:

- Possess a higher rate of self-belief that people like them work in engineering (60.0%, compared to an average 15.0%),
- Are slightly more likely to think that anyone can become an engineer (65.5%, compared to an average 62.7%).

Those with ‘high’ engineering capital not only possessed these more positive images of engineering but also hold more positive attitudes towards themselves and engineering. This group:

- Express a greater belief that engineering is useful to know about (87.7%, compared to the average 48.4%),
- Are less likely to see engineering learning as boring (2.2%, compared to the average of 21.8%),
- Are more likely to believe that engineering learning is good for their own future (88.7%, compared to the average of 38.4%),
- Are more likely to believe they could be successful in engineering in the future (82.3%, compared to the average 29.4%).

These individuals with higher levels of engineering capital are overwhelmingly more positive about engineering, their own abilities and attitudes towards engineering, and their future regarding the engineering domain. Although many of these considerations are not included within the engineering capital instrument, we can see that the possession of engineering capital is associated with an array of positions and characteristics that can support a future engineer. This supports that the engineering capital perspective is indicative of the differences in lived experience in engineering and therefore a valuable lens on engineering inequity.

‘Low Engineering Capital Group’

Those with a ‘low’ engineering capital scored from 0 to 34 on the 0-105 scale of engineering capital. This group represented 19.0% of the 921 participant sample and can be viewed as those who possessed the least resources for engineering and thereby could be understood as the individuals least supported to become an engineer.

This group are disproportionately female (69.0%, compared to the average 56.6%) and from less privileged social backgrounds (22.3% came from ‘very low’ or ‘low’ cultural capital groups, compared to the average of 12.7%).

This group are less likely to have experienced engineering in their lives. They are:

- Less likely to know an engineer (31.2%, compared to the average 48.5%),
- Less likely to have experienced an engineering-related school programme (6.9%, compared to the average 10.5%),
- And are more likely to report having experienced no engineering in their past curricular learning experiences (49.1%, compared to the average 31.6%).

This group are much less likely to align themselves to engineering trajectories. They are:

- Less likely to aspire to engineering education (3.1%, compared to an average of 25.7%),
- Or engineering-related employment (4.8%, compare to an average 35.4%).

Individuals with low engineering capital were less positive about themselves in relation to engineering and less positive about the openness of engineering futures. They report:

- More frequently that people like them are not involved in engineering (70.5%, compared to the average 44.1%),
- A lower belief that they could be successful in engineering in the future (0.6%, compared to the average 31.6%)

- And are less likely to believe that anyone can become an engineer (22.8%, compared to the average 62.7%).

Those with low levels of engineering capital also report more negative learning interest and expectations for engineering. This group are:

- Less likely to think that engineering is useful to know about (13.6%, compared to an average 48.4%),
- More likely to think that learning about engineering is boring (44.1%, compared to an average 21.8%),
- Less likely to think that engineering is a good thing to learn about for their future (10.5%, compared to an average of 38.4%).

The Broader Insights of Engineering Capital

The distinctions identified between the 'high' and 'low' groups demonstrate the wider inequities with which engineering capital is associated. As expected, those in the 'high' engineering capital group possess much greater aspirations for engineering than those in the low group in line with the now proved underlying premise that capital positively aligns to trajectories for engineering. But the distinctions between the 'high' and 'low' groups extend beyond aspirations: differences are also noted in how these groups conceive of, experience and identify with engineering. The ability of engineering capital to discern these differences, without directly examining these topics, demonstrates the central importance and fundamental nature of capital to patterns of inequity. The multifaceted capacity of engineering capital reinforces its value as a model and instrument capable of reflecting deeper characteristics between individuals and groups.

Those in the 'high' engineering capital group more frequently report a recognition of engineering within their curricular learning and greater participation in curricular-mapped engineering experiences. These findings demonstrate that the engineering capital perspective is aligned with formal educational experiences – this is particularly salient given that formal learning experiences were not included within the engineering capital model or instrument due to the limited presence of engineering within UK curricula. This finding has two potential explanations that are not mutually exclusive. First, it is possible that the possession of engineering capital supports learners to recognise engineering within the curricula despite engineering not existing as a distinct curricular subject. Such 're-cognition' is dependent on 'prior cognition' which can later be recollected or found to be familiar (Diana et al., 2006). In this case, the possession of engineering capital implies a grounding of prior cognition that supports recognition of engineering within learning experiences. This explanation would be supported by literature on metacognitive processes which highlight the importance of conscious 'recognition' or 'clarity' in learning. The capacity to 'think about thinking' and find engineering in learning may therefore be influenced by the possession of engineering capital (Dunning et al., 2003). This is consistent with the theoretical structure of engineering capital which includes forms of capital such as consumption of engineering media, talking with others about engineering or the development of engineering literacy which may facilitate learning outside of the classroom which in turn shapes the interpretation of classroom experiences. Given the recognised importance of metacognitive processes to learning this finding suggests that those with engineering capital are capable of more profound and meaningful learning which may subsequently influence learning experiences and achievement for engineering perpetuating patterns of inequity in a Bourdieuian 'social reproductive' fashion.

A second potential interpretation of this greater recognition of engineering amongst those with 'high' engineering capital is that these individuals have experienced a different learning experience within formal education than those with lesser engineering capital. Learning experiences can be shaped by school-based factors such as pedagogical approach or curricular design. Pedagogies involving greater signposting or scaffolding, which may be understood in terms of Vygotsky's 'zone of proximal development', are understood to support a productive learning environment (Shabani et al., 2010). Similarly, discursive peer-led pedagogies introduce the ability for learners to shape the content of formal education. Peer-led discourse or curricular structures may allow engineering to be brought into learning experiences despite its absence within curricula which may explain the greater recognition of engineering amongst those with high engineering capital (Keerthirathne, 2020). This fluidity of curriculum interpretation and provision would be supported by past literature acknowledging the situational factors which shape curriculum delivery (Wang et al., 1990).

This second interpretation is consistent with the confidence and professional qualifications of UK teachers. Only 35.2% of one sample of UK STEM teachers reported they knew a lot about engineering, with only 45.4% feeling confident talking to their students about engineering careers (EngineeringUK, 2020). This lack of engineering confidence amongst teachers is noted elsewhere (Jones et al., 2021; Lewis et al., 2021). As a result, a scarce minority of teachers may be more confident with engineering and capable of integrating engineering learning alongside science, technology, or mathematics curricular experiences leading to greater engineering capital amongst a minority of learners. The greater recognition of engineering within learning experiences by those in the 'high' engineering capital group may in fact be reflecting some deeper nuances in school-based experiences leading to greater engineering capital development. This warrants further investigation with a larger sample to establish if patterns of engineering capital relate to individual teachers or schools to determine the influence of school or teacher factors in the development of engineering capital.

Those in the 'high' engineering capital groups also report a greater participation with engineering curricular-mapped experiences. Such experiences are perhaps the most common form of structured engineering learning offered within UK schools given the lack a distinct curricular subject of engineering but are acknowledged as inequitably offered to learners (Morgan et al., 2016). This association further demonstrates the sensitivity of engineering capital to distinct experiences for engineering learning. As the engineering capital model largely focuses on informal learning contexts further investigation is warranted to examine the distinctions of engineering inequity related to school-based factors such as recognition of engineering or participation with curricular-mapped experiences. Yet the distinction identified between those in 'high' and 'low' groups does demonstrate the sensitivity of the engineering capital instrument to differing classroom experiences highlighting its reach and value.

The comparison of those with 'high' and 'low' engineering capital also identified distinctions in learning related factors demonstrating that the engineering capital instrument is responsive to characteristics relevant to learner dispositions. Engineering capital is found to be positively associated with learning indicators: those in the 'high' engineering capital group possess greater self-identity, self-efficacy, and affective-cognitive engagement with engineering. Self-identity, as an individual's self-appraisal or self-concept, is associated with motivation, academic performance, and academic decision making (Freund & Kasten, 2012; Guay et al., 2004; Hardy, 2014). Self-efficacy, as an individual's belief in their likelihood of future success, is also associated with academic success and academic decision making (Bandura, 1997; Hackett et al., 1992; Honicke & Broadbent, 2016; Pampaka et al., 2011). Affective-cognitive engagement, including value and interest judgements for engineering, are recognised as influential in academic decision making, learning processes and outcomes (Wigfield & Eccles, 2000). The positive association between engineering capital and these learning and success indicators demonstrates the nuance with which the model and instrument relate to the general alignment of an individual with the engineering domain. This further supports the value of engineering capital and supports the importance of these forms of capital in distinguishing the educational experience of young learners.

These wider distinctions identified between those with higher or lower levels of engineering capital demonstrate the broader insights offered by the engineering capital lens. The understanding offered by engineering capital scores is not limited to aspirations but can be used to more broadly comprehend and empirically examine how engineering is experienced by young people in the UK. This further highlights the fundamental character of capital and its significant influence on an individual in line with the work of Bourdieu and Bourdieusian scholars. Further applications are necessary to determine the strength and significance of these further associations, but the strength of differences identified here, in this first application of engineering capital, suggest a meaningful relationship is present. These findings would support that engineering capital offers a more insightful perspective on the nuance and underlying elements of engineering inequities than the often used ‘key performance indicators’ of engineering inequities quoted in contemporary commentary. Engineering capital thereby represents an effective tool to aid the study and intervention of skills shortages and social injustices within the engineering domain supporting the accomplishment of the objective of this thesis.

A confirmation of domain-specific capital model development

The successful formation of a valid engineering capital instrument also legitimises the development methodology adopted to create this novel tool. This process of forming a domain-specific capital model was developed and first applied by Archer et al. (2015) in the creation of the science capital instrument. The successful formation of a second domain-specific capital model using this procedure supports its utility and effectiveness. Little literature, by Archer and colleagues or others, has explicitly outlined and critiqued this instrument development process. The lack of past examination necessitated a critical examination of the process within this thesis. A four-stage process of Bourdieuian conceptual framing, theoretical modelling, empirical instrument formation and validation is outlined and offers a guided insight to the methodology through which the capital perspective can be applied in novel domains. The creation of a successful engineering capital model and instrument in Chapters Four, Five and Six of this thesis thereby represent a unique guidance to the creation of new capital models as a contemporary and practical application of Bourdieuian theory. The detailed adoption and critique of this instrument development process within this thesis offers valuable guidance on the contemporary application of Bourdieuian thinking. Given the ambiguity of the STEM acronym identified within Chapter One and the success of this procedure in forming the science and engineering capital models further applications for the technology and mathematics domains may be valued as further perspectives on STEM inequity.

Conclusions

In this chapter the validity of the engineering model and instrument have been confirmed establishing that the novel development within this thesis is associated with engineering inequities, is consistent with past findings and wields a considerable predictive power on aspirations for engineering trajectories. This approves the developed engineering capital perspective as a lens on engineering inequities and supports the use of the engineering capital instrument to investigate how young learners are supported to become future engineers. Wider reflections on the differences between those with higher or lower levels of engineering capital highlight the broad reach of this perspective, identifying distinctions in how engineering is conceived of, experienced, and related to by young learners. The successful formation of the engineering capital model confirms the integrity of the instrument development model utilised to form this domain-specific Bourdieuian tool. The findings outlined in this chapter articulate the value, novelty and implications of engineering capital as a new tool to understand and address inequitable patterns of access, participation, success and representation within the engineering domain.

CHAPTER EIGHT: FURTHER DIMENSIONS OF ENGINEERING CAPITAL

Introduction

In previous chapters of this thesis a novel model and instrument of engineering capital was developed and validated as a useful lens on engineering inequity. In this chapter this affirmation will continue in recognition that validation is an ongoing process. It is considered that the developed engineering capital model is only the first domain-specific model of capital for the UK engineering domain and that future iterations of the model and instrument may further improve on its scope and application. Five further dimensions of engineering capital will be theoretically and empirically examined as future aspects of engineering capital models. First, two current subcomponents of engineering capital ('engineering literacy' and 'knowing an engineer') will be revisited to outline the value offered by investigating and improving existing elements of engineering capital. Second, two new subcomponents of engineering ('familial capital' and 'linguistic capital') will be explored as further aspects of engineering capital. Finally, a novel application of engineering capital will be explored to determine the usefulness of applying engineering capital to learning experience in classroom settings. Commentary on empirical findings will outline future avenues of iteration and research enquiry to strengthen understanding of engineering inequities in the UK.

Iterating Engineering Capital

Although the engineering capital model developed within this thesis has been validated as a useful lens on engineering inequity it is important to recognise that this model is only one possible Bourdieuian model of capital in the engineering domain. If the four stage instrument development process adopted in this thesis was completed using other forms of capital, or if a distinct development approach was adopted, then it is likely that the resulting tool would differ from the exact model of engineering capital created in this thesis. Whilst it would be expected that any model of Bourdieuian capital would follow the same underlying premise - that those with greater capital are better supported to succeed – it is possible that the accuracy and value of these distinct models may differ. As a result, we must accept the possibility that this first engineering capital model is not optimal and that future iterations of engineering capital must be investigated to ensure maximum utility in understanding and addressing engineering inequities.

Such a strategy of ongoing iteration is consistent with the practices of instrument development outlined in published literature that recognise validation as an ongoing process to confirm lasting validity in a changing world (Benson & Clark, 1982; Streiner & Kottner, 2014). A need to iterate and adapt to changing contexts is also consistent with the interpretation of the Bourdieuian framework adopted in this thesis (outlined in the Methodology chapter) which acknowledges the need to apply Bourdieuian thinking in a contemporary fashion: to challenge the primacy of 'high arts' in understanding 'legitimate' culture, to apply the lens in a granular fashion to specific domains, and to acknowledge the malleability of capital over time (Archer et al., 2015; Prieur & Savage, 2013; Sullivan, 2001). This interpretation fundamentally acknowledges the changeability of capital which rationalises an iterative strategy of deployment that can be responsive to change over time. An iterative approach to supporting engineering capital is thereby consistent with both the best practices of instrument development and the core framework of this model.

Multiple approaches of iteration could be adopted to ensure the ongoing validity and maximum utility of engineering capital. These approaches may include revisiting the existing subcomponents of engineering capital, the introduction of new elements into this model or the application of engineering capital to novel contexts to widen its span of application. Each approach would represent a re-examination of capital within the engineering domain that would support the value of engineering capital and its use to understanding inequity. In the following chapter each of these three strategies will be adopted to identify future avenues of investigation and iteration of engineering capital.

First, to test the iteration of improving existing elements of engineering capital two current subcomponents ('engineering literacy' and 'knowing an engineer') will be revisited. Second, to test the iteration of introducing new elements of engineering capital two new forms of capital ('familial capital' and 'linguistic capital') will be explored in relation to the engineering domain. Finally, to test a further application of engineering capital beyond its focus on future engineering trajectories the association between engineering capital and learner engagement will be examined to determine the relevance of this model to classroom settings. Each of these five considerations will be theoretically and empirically explored to identify avenues of iteration to improve upon the engineering capital model and instrument developed in this thesis.

Revisiting Existing Subcomponents of Engineering Capital

The seven subcomponents of engineering capital (outlined in Chapter Five) represent the sum of inputs that are considered as aspects of capital in this model and instrument. These three forms of cultural capital, two forms of social capital and two forms of behaviours and practices were theoretically supported by past literature as compatible with a domain-specific application of Bourdieuian capital and supported by wider literature as relevant to the engineering domain (Archer et al., 2015). Future iterations of engineering capital may seek to improve upon the framing of these seven subcomponents through re-examination of the scope, structure or operationalisation of these forms of capital.

‘Engineering Literacy’ and ‘Engineering Habits of Mind’

Within this thesis ‘engineering literacy’ is understood as a sufficient possession of engineering knowledge, skills and ways of ‘thinking’ and ‘doing’ in the engineering domain. The ‘ways of thinking and doing’ within this conceptualisation refer to habits of mind: the ways in which engineering is embodied within the individual, their thought processes and actions. An individual in possession of engineering habits of mind will think and act in a manner that is characteristic of an engineer. Habits of mind have been used to not only understand literacy and intelligence (Costa & Kallick, 2000) but also as an approach to structuring learning and its outcomes (Campbell, 2006; Costa & Kallick, 2008). Though models of engineering literacy are rare several acknowledge the importance of habits of mind to a conceptualisation of the ‘literate engineer’ (Chae et al., 2010; Huffman et al., 2018). Within the engineering capital subcomponent of ‘engineering literacy’ this is operationalised with items examining engineering qualities such as imagination or understanding of how to design and make, but the substantial span of this initial theoretical model of engineering capital limited the degree to which engineering habits of mind could be explored.

Given the theoretical recognition of habits of mind within models of engineering literacy future iterations of engineering capital may wish to further examine the association between this model and engineering habits of mind. One significant body of literature from the UK context that may be drawn on to inform this further examination is that of Lucas and Hanson who identified six engineering habits of mind: creative problem solving, improving, problem finding, adapting, visualising, and systems thinking (Lucas & Hanson, 2014; Lucas & Hanson, 2018; Lucas et al., 2014). These habits of mind are outlined in Table 8.01 below.

Table 8.01: Lucas and Hanson’s Engineering Habits of Mind and summarised definitions.

Habit of Mind	Summarised Definition
Creative Problem Solving	The generation of ideas and solutions through cross-cutting, critiquing, and working as a collective.
Improving	The enhancement of things through experimentation, design processes, experimenting and testing.

Problem Finding	The development of questions and hypotheses, testing of existing solutions, and strategic verification of results.
Adapting	The reworking of existing things to novel contexts or purposes through modification or change.
Visualising	The imagining of abstractions, conceptualisations, and processes through which these may be operationalised.
Systems Thinking	The cross-cutting structuring of connections and interrelations between things, identification of patterns, and elemental interactions within holistic structures.

Though such habits of mind are recognised within the theoretical model of engineering capital the six habits identified by Lucas and Hanson could not be operationalised in the formation of engineering capital due to the risk of skewing the 'engineering literacy' measurement with six items addressing habits of mind. This omission was further supported given the limited replication of this model of engineering habits of mind amongst secondary school learners - it was necessary to only generalise habits of mind within the formative model and relegate a further investigation to post-formation where the relationship between these habits of mind could be better established in relation to a structured model of engineering capital. Now that a complete model of engineering capital has been formed it is possible to investigate how engineering habits of mind relate to this model to determine the relevance of these six attributes to patterns of engineering inequity. Given the significant role of engineering literacy within the now validated measure of engineering capital it would be expected that engineering habits of mind are also positively associated with greater engineering capital and trajectories for future engineering. This examination would represent an elaboration of the engineering literacy subcomponent within the engineering capital perspective.

'Knowing an Engineer' and 'Knowing a Hobbyist Engineer'

The 'knowing an engineer' subcomponent of engineering capital is identified as a form of social capital relevant to the engineering domain. This relationship is argued to potentially benefit a young learner through access to resources that positively impact learning and aspirations (Cheryan et al., 2011) with this benefit identified in both national and international study of the engineering domain (Plasman et al., 2021; Takruri-Rizk, et al., 2008; Zhang, 2021). Within the model of engineering capital 'knowing an engineer' is framed in relation to employment; parental employment is identified as particularly salient, with 8.6% of one UK sample of engineers possessing an engineer parental figure (Laurison & Friedman, 2016). However, the opportunity to iterate the engineering capital model presents the opportunity to reflect further and expand our understanding of how social relationships may influence engineering inequities. It should be recognised that engineering is not only an occupational practice but can be embodied and actioned in non-professional contexts. It may therefore be relevant to consider a subcomponent of ‘knowing a hobbyist engineer’: someone who participates in non-employment practices of engineering within their lives in a more recreational fashion.

Little contemporary literature has examined the benefits of access to engineering hobbyists in the UK context but the underlying premise of social capital in the engineering capital model (that close social connections to engineering provide a potential resource to young learners) is theoretically applicable to hobby activity. ‘Play activity’ has long been recognised in literature examining the patterned participation of young learners with engineering (Cooper & Robinson, 1989). A wider body of literature has explored ‘making’ as non-occupational practices of engineering (Graham & Crawley, 2010; Vossoughi & Bevan, 2014). These ‘civilian engineers’ frequently possess engineering educational or career backgrounds, which suggests a degree of interconnectivity between ‘knowing an engineer’ and ‘knowing a hobbyist engineer’ (Foster et al., 2018). However, making is acknowledged as also inclusive of artistic backgrounds demonstrating a distinctiveness to ‘knowing a hobbyist engineer’ (Foster et al., 2018). This is relevant to the scope of engineering capital and its consideration of social capital influences as it widens the social network that is recognised to be of influence. ‘Knowing a hobbyist engineer’ was omitted from the formative model of engineering capital due to the relative lack of past examination of social connections to hobbyist engineers within capital-based models. Where other subcomponents of engineering capital had been applied to specific domains within the work of Archer et al. (2015) ‘knowing a hobbyist scientist’ was not explicitly included lowering the threshold of certainty that this form of capital was appropriate for domain-specific examination. This subcomponent also highlights the risk of generalising across domains and the value of developing distinct domain-specific models of capital: as a more practice-led domain it is likely that engineering features more within hobbyist activities than the more theoretical or intellectual domain of science. This would suggest a greater relevance of ‘knowing a hobbyist’ to the engineering domain that would support its inclusion in an engineering capital model. This thereby supports the investigation of ‘knowing a hobbyist engineer’ as a feature in future iterations of engineering capital.

Investigating New Subcomponents of Engineering Capital

Future iterations of engineering capital may look beyond the seven subcomponents of the formative model to consider further forms of capital within the engineering domain. The seven subcomponents of the engineering capital model were chosen, in part, due to the support of past literature which validated their application in domain-specific models of capital (Archer et al., 2015). Further forms of capital would not require this support as their relevance could be established directly in relation to the now formed engineering capital model. Wider applications of Bourdieuian thinking within past literature can be drawn upon to inform these next subcomponents of engineering capital. The work of Yosso (2005) is a strong example of how the Bourdieuian framework can be drawn upon, critiqued and adapted to novel applications. Yosso's 'Community Cultural Wealth' model questions the underlying narrative of white, male, middle class dominance within the Bourdieuian perspective and introduces the consideration of forms of capital held by those Bourdieuian social reproduction would characterise as 'non-dominant'. This interpretation acknowledges that particular groups may possess their own bodies of capital in response to their social position. This alternative take on Bourdieuian capital is consistent with the position adopted in this thesis that considers the capitals found within particular domains. The 'Community Cultural Wealth' model identifies many forms of capital including: aspirational capital, familial capital, navigational capital, resistant capital, and linguistic capital. Two of these (familial capital and linguistic capital) will be considered as potential forms of capital for future iterations of engineering capital.

Familial Capital

Familial capital is framed by Yosso (2005) as the "cultural knowledges nurtured among familia (kin) that carry a sense of community history, memory and cultural intuition" (p79). This form of capital is noted to relate beyond immediate family contexts to wider kinship and community and the history and collective experience which binds them. In this way familial capital may be understood as somewhat related to the concept of habitus as a system of dispositions, or way of being, that is developed through mimesis from early social environments and shapes ways of thinking, interpreting and acting (Wacquant, 2005). However, familial capital also extends beyond habitus and its role as a structuring 'lens' to consider the oppositional distinctiveness of community culture (in relation to a dominant other culture) and the resources that can be drawn from this community identity and experience. Whilst it is likely that habitus and familial capital interact the forms of capital offered through a community and its historical context are theoretically distinct. The concept of familial capital is also relevant to the concept of social capital: both are concerned with wider group connections and their influence on access to capital. However, where social capital is concerned with "the sum of resources, actual or virtual" within a network familial capital relates to the forms of capital inherent to a particular community that develop in relation to the dominance of another culture (Bourdieu & Wacquant, 1992, p119). Familial capital can thereby be possessed by an individual and does not depend on the potential access facilitated by another highlighting its conceptual distinctiveness. Familial capital then is offered as a conceptual perspective on local community and culture that is distinguished from the dominant and prevalent status quo.

Familial capital may hold a relevance to the engineering domain and its relationship to community. Engineering can be understood as possessing a limited presence within the contemporary culture of UK society. Whilst engineering contributes greatly to the UK economy public literacy and identity with engineering is limited (EngineeringUK, 2018; Institution of Mechanical Engineers, 2016; Institution of Mechanical Engineers, 2017; Marshall et al., 2007). However, familial capital provides the opportunity to move beyond a national generalisation to focus on both a local and historical framing of engineering and the impact of belonging to a community with an engineering connection. The local and historical perspective on engineering is highly relevant to the UK and its past as a goods-based, engineering industry active nation (Buchanan, 1985; Hudson & Hudson, 1989). It seems relevant to consider that particular regions, perhaps dominated by engineering industry in the present or past, may carry some 'community history, memory and cultural intuition' which interacts with engineering inequities. Communities such as Sheffield (once and presently connected with the steel industry), Leyland (once dominated by the automotive industry) or the Black Country (once dominated by mining) may carry familial capital for engineering which distinguishes these regions from others that lack this connection to the domain. Engineering familial capital may represent an important dimension of engineering inequity that is largely absent from contemporary study. An understanding of these 'pockets' of familial capital may offer a perspective on inequity and may offer a perspective on the national engineering inequities in the UK through a historical or geographic lens.

The initial thesis sample was insufficient to infer familial capital through regional comparisons but following the creation of the engineering capital instrument it is now possible to examine the association between familial capital and engineering capital scores with a less geographically represented sample. It is expected that familial capital for engineering will be positively associated with engineering capital – if this is proved through further analysis then this would support the inclusion of familial capital in future research and iterations of engineering capital.

Linguistic Capital

Linguistic capital is framed by Yosso (2005) as "the intellectual and social skills attained through communication experiences in more than one language and/or style" (p78). This form of capital supports the generalisable benefit of proficiencies that develop through the use and engagement with multiple languages or styles. This is not a radical adoption of Bourdieuian capital with Bourdieu noting the importance of language and its relationship with capital (Bourdieu, 1991). Language use may be understood as a deeply complex: language use not only requires a knowledge of words and their meaning but an understanding of the rules of grammar, socialised practices of use, and coded representation of the self to others. Yosso explores this in relation to communities of colour noting that bilingual or multilingual groups will carry distinct linguistic experiences with "memorization, attention to detail, dramatic pauses, comedic timing, facial affect, vocal tone, volume, rhythm and rhyme" (p79) or artistic expression through art, music or poetry. Whilst the engineering domain does not involve a distinct language it may be recognised that engineering carries its own vocabulary and style that distinguishes it from common use of language. The benefit of general linguistic capital may therefore extend to the engineering domain in such a way that those with greater capital are more comfortable and capable of engaging in engineering culture. Alternatively, engineering-specific linguistic capital may be examined in relation to linguistic ability in relation to the engineering domain. As noted earlier, the development of the engineering capital model now facilitates the examination of wider forms of capital that have previously not been examined in relation to specific domains. Further investigation is required to establish the relevance of linguistic capital to the engineering domain and the role of this form of capital in future iterations of engineering capital.

Further Applications of Engineering Capital

The iteration of engineering capital also provides the opportunity to consider broader applications of this model. The possibility that engineering capital may possess wider utility beyond its specific application in this thesis is supported by the foundational importance and influence of capital within the Bourdieuian framework (Bourdieu, 1986). Although developed to better understand engineering inequities amongst young learners, particularly in relation to aspiration for future engineering education or careers, the validation analyses in Chapter Seven also identify strong associations between the model and learning indicators such as identity or engagement. This suggests that engineering capital is relevant not only for 'future-orientated' inequities such as engineering aspirations/trajectories but might also support understanding of 'presently-active' inequities currently acting on young learners within classroom settings. The findings outlined in Chapter Seven demonstrate that those with greater levels of engineering capital reported lesser boredom with engineering learning, higher self-belief for engineering, and higher outcome expectations for future engineering.

Each of these characteristics can be understood as aspects of learner engagement: the alignment and investment of a learner to a learning experience that bridges an array of psychological characteristics. Definitions of engagement are notably varied with Fredricks et al. (2004) identifying characteristics such as learner commitment, participation, or involvement in learning. The engagement concept is explored in three strands of research considering the affective, behavioural and cognitive aspects of engagement. Affective engagement considers the emotional characteristics of learner alignment to learning including attitudes, interests and values such as interest, enjoyment, boredom, anxiety or happiness (Kahu et al., 2017; Pekrun & Linnenbrink-Garcia, 2012; Wigfield & Eccles, 2000). Behavioural engagement is concerned with observable qualities of learner alignment to learning which may include behaviours expressed in the classroom such as task attention, participation with discourse, or wider participation in informal learning (Finn & Zimmer, 2012; Hospel et al., 2016). Cognitive engagement explores the investment of learners to the process of learning and the deployment of attention and effort to accomplish learning outcomes, including motivations, metacognitive processes or learning strategies (Blumenfeld et al., 2012; Lawson & Lawson, 2013). These perspectives on engagement are not exclusive, with engagement recognised as a ‘meta-construct’ (Lam et al., 2012). Engagement is positively associated with participation, persistence and achievement in education (Appleton et al., 2008; Dotterer & Lowe, 2011; Northey et al., 2018). A lack of engagement, at times referred to as ‘disaffection’, is associated with learners who express a lack of persistence, interest or enjoyment with learning that subsequently impacts achievement (Skinner et al., 2008; Skinner et al., 2009). Though noted as carrying some degree of ‘conceptual haziness’ (Appleton et al., 2008) the meta-construct of engagement is a powerful tool within the study of learners, pedagogy, curricular design and learning experiences. Its recognised malleability ties the concept not only to a status quo but to intervention and change leading to many intervention evaluations utilising aspects of engagement (Fredricks et al., 2004; Virtanen et al., 2015).

Engineering engagement can therefore be understood as the alignment and investment of young people to learning in the engineering domain. Whilst a relationship between engineering capital and engineering engagement is suggested in the analyses of Chapter Seven further examination is required to confirm the association and support the wider application of engineering capital to understanding patterns of learner engagement. The confirmation of the expected positive association would support the use of engineering capital to understand inequities within current learning experiences and the application of this model within school settings.

Having theoretically identified five further aspects of engineering capital that may hold value to future iterations of this model next these aspects will be empirically examined to determine their statistical relevance to the engineering capital model.

Chapter Research Methods

Methodology

The research enquiry of this chapter is concerned with the relationship between engineering capital, as a validated lens on inequity, and the investigation of five further dimensions of engineering capital which may feature in future iterations of this model. To investigate this a theoretical and empirical approach was adopted to explore the five further dimensions and their association with engineering capital. This approach dictates a quantitative empirical methodology to statistically examine the relationship with the quantitative engineering capital instrument and further dimensions of engineering capital measured in a similarly quantitative manner and recorded in the thesis dataset. As noted within the Methodology chapter, the lingering impact of the Covid-19 pandemic dictated only a single point of contact with participants necessitating the collection of data on these five speculative dimensions of engineering capital within the initial dataset. Drawing on the same sample for both the formation and further investigation of engineering capital limits extraneous sampling effects and supports the validity of these further insights.

Participants

Data was collected from 921 secondary school-aged (11 to 16 years old) learners from ten schools in England and Scotland. As noted in the Methodology chapter, a single point of data collection was adopted for this thesis research project due to the demands of the Covid-19 pandemic. The sample of 921 learners examined in this chapter is the same sample examined throughout the thesis. See Methodology chapter for full outline of sample characteristics and rationale for the selected participant population.

Instruments

Instruments were developed or adopted to empirically measure the following amongst participants: engineering capital, engineering habits of mind, knowing a hobbyist engineer, familial capital, linguistic capital, and engineering engagement. These instruments are outlined below.

Engineering capital: The 11-item engineering capital instrument created and outlined in Chapter Six was adopted to calculate the engineering capital of participants. Item responses are tallied to form a single engineering capital score for each participant on a scale of 0-105. Engineering capital scores were used to code participants as possessing low (0-34), medium (35-69) or high (70-105) levels of engineering capital. This division of the response scale into thirds was adopted from Archer et al.'s (2015) science capital development process and the definition of science capital groups within the science capital literature. A direct adoption of this approach would support comparison with science capital scores and was justified as an efficient and objective approach to distinguishing those with greater or less engineering capital. The use of this approach in Chapter Four within the Archer-style engineering capital instrument also provides the opportunity to cross-compare Bourdieuian capital models. See Chapter Six for further details on this instrument.

Engineering habits of mind: A six-item instrument of engineering habits of mind was developed drawing on the work of Lucas and Hanson (2016). Six items were developed, one item for each of Lucas and Hanson's model of engineering habits of mind, and analysed for reliability and validity. A Cronbach's Alpha analysis confirmed the internal consistency of items (N=897, a=0.850). An unrotated Principal Components Analysis supported that the instrument was structured as expected supporting the validity of this instrument (see Appendix H for statistical outputs). The Likert scale responses of each item were converted to a score of -2 to 2 and tallied to calculate a total engineering habits of mind score on a scale of -12 to 12.

Table 8.02: Engineering Habits of Mind instrument items and response scales.

Item	Response Scale
I am good at finding patterns and seeing how things fit together	-2 to 2 five-point Likert scale
I am good at looking for problems and checking things are right	-2 to 2 five-point Likert scale
I am good at imagining and picturing what things might look like	-2 to 2 five-point Likert scale
I am good at trying ways to make things better	-2 to 2 five-point Likert scale
I am good at fixing problems and finding solutions	-2 to 2 five-point Likert scale
I am good at trying things, testing ideas and changing my plans if necessary	-2 to 2 five-point Likert scale

Knowing a hobbyist engineer: Three items were developed to examine the degree to which an individual knew hobbyist engineers. Participants were asked if they knew such a hobbyist, their relationship to this individual or individuals, and the hobby these social contacts participated in. Responses were scored with parental connections weighted more heavily (scored as two) whilst other social contacts were scored as one. Three possible responses were recorded and tallied to calculate a knowing a hobbyist engineer score of 0-6. Following free response data collection hobbies were thematically analysed and coded as: arts, automotive, beauty/hair, crafts (general), culinary, design (general), digital/electronic, garden, home/repair, mechanical, metalworking, occupational, textiles, woodworking.

Table 8.03: Knowing a hobbyist engineer instrument items and response scales.

Item	**Response Scale**
Do you know someone (friend, family, someone from your community) who has a hobby that involves engineering?	Yes, No, Don't know
You said you know someone among your friends, family, or community who has a hobby that involves engineering, can you tell us who they are?	Free response. Later coded as 'parent or guardian' (scored as two) or otherwise scored as one.
And what hobby do they do?	Free response. Later coded as outlined above.

Engineering familial capital: Two items were developed to examine the engineering domain-specific familial capital of young learners. These items drew on Yosso's (2005) community cultural wealth model and wider reading on familial capital (Sablan, 2019) to examine kin (family and community) historic ties to engineering. The Likert scale responses of each item were converted to a score of -2 to 2 and tallied to calculate a total engineering familial capital score on a scale of -4 to 4.

Table 8.04: Engineering familial capital items and response scales.

Item	**Response Scale**
There is a history of engineering within my local community	-2 to 2 five-point Likert scale
There is a history of engineering within my family tree	-2 to 2 five-point Likert scale

Linguistic capital Four items were developed to examine the both the general and engineering-specific linguistic capital of young learners drawing on Yosso's (2005) positioning of linguistic capital and wider application of this concept (Gerhards, 2014; Sablan, 2019). Two items were used to calculate a general linguistic capital score. Participant proficiency with languages other than English were queried and responses scored on a scale of zero to three. Three possible responses were noted and scores tallied to produce a general linguistic capital score of 0-9. Two items were used to calculate an engineering-specific linguistic capital score. Likert-scale responses for these two items were converted to a score of -2 to 2 and tallied to calculate a total engineering-specific linguistic capital score of -4 to 4.

Table 8.05: Linguistic capital items and response scales.

Item	**Response Scale**
General Linguistic Capital	
Can you speak or read a foreign language other than English?	Yes/no
If yes, what language and how well?	Free response, and multiple choice: I know a little, I know a lot, I am fluent
Engineering-Specific Linguistic Capital	
I know how to talk about engineering using technical words and language	-2 to 2 five-point Likert scale
I am comfortable having conversations about engineering	-2 to 2 five-point Likert scale

Engineering engagement: A twelve-item instrument of engineering engagement was developed drawing on wider engagement literature (Eccles & Wigfield, 2002; Fredricks et al., 2004; Kosovich et al., 2015; Lent et al., 2002). These items explored affective and cognitive dimensions of learner engagement identified in past literature. A Cronbach's Alpha analysis confirmed the internal consistency of this novel engagement instrument (N=851, a=0.922). An unrotated Principal Components Analysis was utilised to examine the dimensionality of this novel measurement instrument. This analysis resolved to two components: one that included almost all items and a second that related only to the three reverse-coded items. This suggests that engagement and disengagement/disaffection are not bidirectional but two distinct but related characteristics (see Appendix H for statistical outputs). Whilst theoretically interesting this is consistent with the conceptualisation of engagement within this thesis and wider literature (Skinner et al., 2009) supporting the use of this instrument as a broad measure of cognitive and affective engagement/disengagement with the engineering domain. Likert-scale responses for these twelve items were converted to a score of -2 to 2 and tallied to calculate a total engineering engagement score of -24 to 24.

Table 8.06: Engineering engagement items, the dimensions of learning engagement they represent, and response scales.

Item	Dimension of Learner Engagement	Response Scale
I believe I could be successful at engineering in the future.	Self-efficacy	-2 to 2 five-point Likert scale
I know quite a lot about engineering.	Self-concept	-2 to 2 five-point Likert scale
I think understanding engineering is important.	Attainment value	-2 to 2 five-point Likert scale
I enjoy learning about engineering.	Intrinsic value – enjoyment	-2 to 2 five-point Likert scale
I think learning about engineering is interesting.	Intrinsic value – interest	-2 to 2 five-point Likert scale
I think it is useful to know about engineering.	Utility value	-2 to 2 five-point Likert scale
Learning about engineering takes too much effort (reverse coded).	Cost value	-2 to 2 five-point Likert scale
I think learning about engineering is boring (reverse coded).	Negative affect – boredom	-2 to 2 five-point Likert scale
I worry I am not good at engineering (reverse coded).	Negative affect – anxiety	-2 to 2 five-point Likert scale
I want to learn more about engineering.	Curiosity	-2 to 2 five-point Likert scale
I want to learn more about engineering even if it is hard.	Persistence	-2 to 2 five-point Likert scale
It would be good for my future to learn about engineering.	Outcome expectations	-2 to 2 five-point Likert scale

Procedure

The questionnaire instrument was designed, developed, and applied for data collection as outlined in the Methodology chapter. Following data processing and cleaning the thesis dataset was examined to analyse the relationship between engineering capital and the five further concepts outlined above.

Descriptive statistics and one way ANOVA analyses were adopted to examine the relationship between the independent variable of engineering capital groups (low, medium, high) and scores on the engineering habits of mind, knowing a hobbyist engineer, familial capital, linguistic capital and engineering engagement instruments. The adoption of these tests is appropriate for group-based comparisons (Ho, 2013). Statistical assumptions were met supporting the use of these methods.

Results and Discussion

Engineering Habits of Mind

A Welch's one-way ANOVA analysis examined the difference in engineering habits of mind scores between engineering capital groups (low, medium, high engineering capital scores). This analysis identified significant differences between groups ($F(2, 214.224) = 89.394$, $p<0.001$, $ETA^2=0.154$) with Games-Howell post-hoc testing confirming differences between group mean habits of mind scores at all levels (Low: M=0.83, SD=4.26; Medium: M=3.79, SD=3.55; High: M=6.67, SD=2.80) (see Appendix H for statistical outputs).

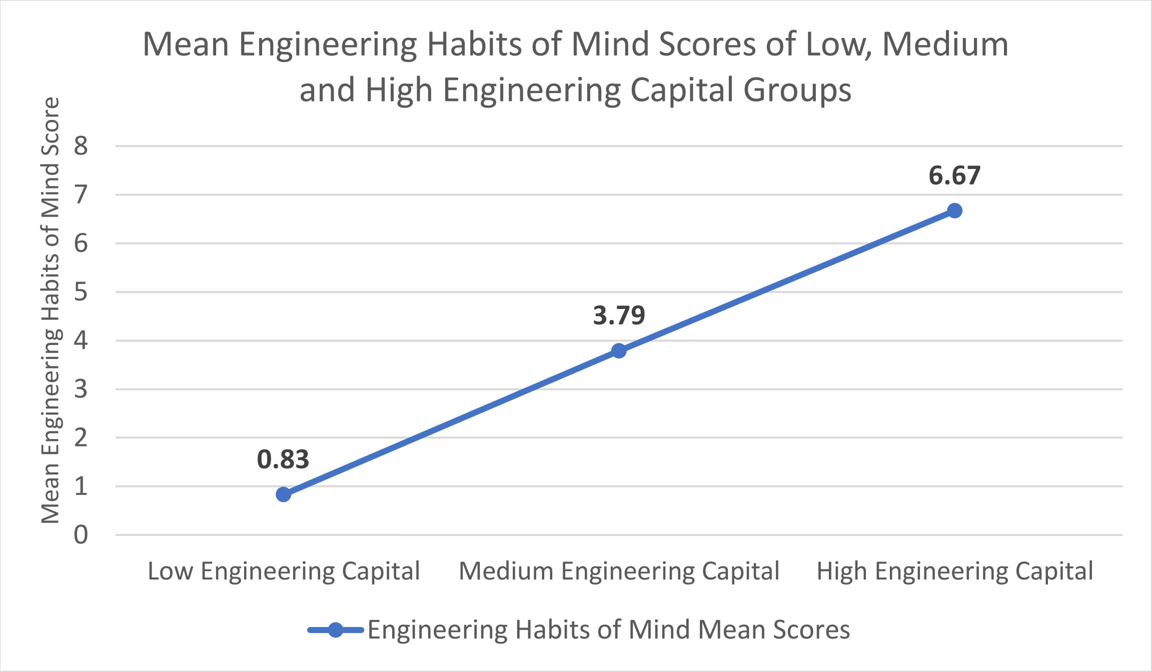

Figure 8.01: Mean engineering habits of mind scores of high, medium and low engineering capital groups.

These results confirm the expected positive association between engineering capital and the engineering habits of mind subcomponent: those with greater engineering capital self-report a greater possession of engineering habits of mind. This was expected given that engineering habits of mind were already, in limited terms, included within the 'engineering literacy' subcomponent of the engineering capital model. The analysis outlined above demonstrates that the engineering capital instrument is representative of engineering habits of mind despite its limited measurement of these habits within its instrument. This supports the potential addition of engineering habits of mind within future engineering capital models and instruments. These results also offer a further validation of Lucas and Hanson's (2016) engineering habits of mind model that was operationalised in this analysis. The significant relationship between engineering capital and engineering habits of mind demonstrates a link between Lucas and Hanson's model and engineering inequities. Further research may investigate how engineering habits of mind are distributed amongst young learners in relation to engineering inequity and the impact of these habits on trajectories to engineering education or careers.

The positive association between engineering capital and Lucas and Hanson's engineering habits of mind further supports the position adopted in this thesis that engineering capital is a malleable concept that is capable of being intervened with to address inequity. As noted in the Methodology chapter, this thesis recognises the dynamic nature of Bourdieuian capital and the capacity for individuals to develop forms of capital through intervention. This is compatible with the work of Lucas and Hanson who similarly saw engineering habits of mind as malleable. These researchers put forward potential pedagogical structures that can support the development of engineering habits of mind, such as: adjustments in how teachers communicate, the presentation of opportunities for discourse, the use of graphic representations or problem-based learning (Lucas et al., 2014). This is consistent with wider literature that acknowledges the relevance of habits of mind to learning and teaching strategy (Campbell, 2006). This conceptual compatibility supports the position that engineering capital is capable of change given its alignment to changeable qualities. Engineering habits of mind, as an aspect of engineering literacy, represent cultural capital for engineering that are capable of being developed over time. Not only does this compatibility further support the inclusion of engineering habits of mind within future iterations of the engineering capital model but also suggests strategies through which engineering inequities may be addressed. The interventions proposed by Lucas and Hanson (2016) may also support the development of engineering capital: increases in engineering habits of mind would represent improvements in the engineering cultural capital of engineering literacy.

However, deeper reflection on the development of Lucas and Hanson's (2016) model also introduces an issue that must be contended with before these habits of mind can be iterated into the engineering capital model. Lucas and Hanson's (2016) model of six engineering habits of mind was developed though mixed methods (interviews, focus groups, and questionnaires) with engineering educators and engineering experts. Bourdieu notes that institutions, and those in service of institutions, will carry a conceptualisation of the ‘legitimate’ culture within that institution. This issue is contended with in Chapter One of this thesis when framing a definition of engineering. Given that the habits of mind identified by Lucas and Hanson were generated by those within engineering institutions it may be that these habits of mind are the ones recognised as ‘legitimate’ and thereby are an exclusionary conceptualisation that neglect more diverse ‘ways of thinking and doing’ that exist in the engineering domain. This would suggest that the inclusion of these habits of mind within future iterations of engineering capital may perpetuate inequity rather than address it. This warrants further examination to determine whether these habits of mind represent a way of thinking and doing engineering that is accessible and not in service of perpetuating the same types of groups dominating the engineering domain. Further study with larger samples drawn from more diverse backgrounds may aid in this analysis. The inclusion of engineering habits of mind within future iterations of engineering capital should be cautious or seek to answer this question in its formation.

Knowing a Hobbyist Engineer

Cross-tabulation calculations were applied to compare responses to the question “Do you know someone (friend, family, someone from your community) who has a hobby that involves engineering?” against low, medium, and high engineering capital groups. These results are outlined in Table 8.07 below.

Table 8.07: Cross-tabulated results to knowing a hobbyist engineer for overall sample and categorised by engineering capital groups.

Engineering Capital Group	**Responses**		
	‘Yes’	‘Don’t Know’	‘No’
Low	38.3%	21.1%	40.6%
Medium	56.7%	20.3%	23.0%
High	68.9%	10%	21.1%
Overall Total	**54.4%**	**19.4%**	**26.2%**

These cross-tabulations show that those with ‘high’ engineering capital possess an above average rate of ‘yes’ responses and below average rate of ‘don’t know’ and ‘no’ responses with the reverse true for those with ‘low’ engineering capital. A chi-square test was applied to test the association between engineering capital groups and knowing a hobbyist engineer. The test revealed a significant association ($X^2(4) = 34.084$, $p<0.001$, Cramer’s V=0.137) with Cramer’s V effect size statistic indicating a substantive relationship between variables. These findings confirm the expected positive association between engineering capital and knowing a hobbyist engineer consistent with other identified social capitals within the engineering domain (see Appendix H for statistical outputs).

Given the limited body of literature examining the impact of social connections to hobbyist engineers in the UK context two further chi-squared tests were deployed to further examine the associations between these social connections and social characteristics of gender and social class. Both tests revealed no significant association between knowing a hobbyist engineer and gender ($X^2(2) = 1.819$, p=0.403, V=0.046) or social class ($X^2(8) = 7.501$, p=0.484, V=0.64) – it should be noted that the social class test did not meet all test assumptions questioning the validity of its conclusion and should be re-examined with a further sample. See Table 8.08 for cross-tabulations (see Appendix H for statistical outputs).

Table 8.08: Cross-tabulated results to knowing a hobbyist engineer for gender and social class groups.

Grouping	**Responses**		
	'Yes'	'Don't Know'	'No'
Gender			
Boy	52.9%	21.8%	25.3%
Girl	56.9%	18.5%	24.6%
Social Class (cultural capital group)			
Very low	50.0%	20.0%	30.0%
Low	50.5%	22.9%	26.7%
Medium	51.3%	21.5%	27.2%
High	58.8%	18.7%	22.5%
Very high	61.6%	16.5%	22.0%
Overall Total	**54.4%**	**19.4%**	**26.2%**

Cross-tabulated responses to the question "And what hobby do they do?" were also examined. No trend emerged within coded responses with little variation in the types of hobbies engaged in by the hobbyists known by low, medium and high engineering capital groups. However, the sample of this thesis is notably small to examine trends in such a widely coded set of responses (14 possible forms of hobby are noted) supporting the need for future study with a more representative sample to more confidently report the consistency of hobbies engaged in by social contacts of differing groups.

The confirmation that those with greater engineering capital also possess significantly greater social connections to hobbyist engineers is consistent with the underlying Bourdieuian framework of engineering capital. This supports the inclusion of knowing a hobbyist engineer as a further dimension of engineering capital and topic for further study in future iterations of the model and instrument. Those with greater social connection to a hobbyist engineer will, according to Bourdieuian social capital, possess greater potential access to resources offered through that social relationship (Bourdieu & Wacquant, 1992). A hobbyist engineer may provide young learners with access to formative experiences with engineering that are beneficial given the scarcity of engineering within national curricula. Early experiences are recognised as deeply influential for the development of interest and aptitude supporting the significance of knowing a hobbyist engineer in formative years (Katz, 2010). Knowing a hobbyist may also offer an early role model to support the development of an engineering identity or engineering characteristics within a young learner (Lucas et al., 2014; Sonnert, 2009). Given the recognition by Foster et al. (2018) that "makers", frequently possess some degree of educational or career experience with engineering it is possible that hobbyists may act as a source of guidance to young learners in how to navigate trajectories towards future engineering education or careers. Further research is warranted to examine the deeper nuances and potential benefits on offer through a social connection to a hobbyist engineer but the results outlined here indicate support for the inclusion of this form of capital in future iterations of engineering capital.

It is notable that despite the positive association identified between knowing a hobbyist and the possession of engineering capital there are no significant associations identified between knowing a hobbyist and either gender or social class groupings. This is at odds with the expected pattern of inequities within the engineering domain which might predict that social connections to hobbyists differ for these groups. The lack of gender difference is particularly surprising given the strong differences in engineering capital identified for gender groups in earlier chapters. However, this finding can also be acknowledged as consistent with the underlying perspective of Bourdieuian social capital which notes that an individual must possess both a resource within their social network and the means to access that resource in order to benefit from this form of capital. It may be that many groups possess a social connection to engineering-related hobbies, but not the means to benefit from that resource. A certain volume of engineering capital may be required in order to benefit from, or access, further forms of capital. This is a reasonable assertion: a somewhat strong understanding of engineering (engineering literacy) may be required in order to meaningfully engage with an engineering club (engineering out-of-school learning) or understand the engineering aspects of a parent's occupation (knowing an engineer).

These findings highlight both the complexity of ‘knowing a hobbyist’ but also further supports the validity of the engineering capital model and instrument developed in Chapters Five to Seven which was found to be associated with knowing an engineering hobbyist. A significant association with engineering capital does, despite this complexity, demonstrate that knowing a hobbyist engineer is relevant to inequities in the engineering domain. This demonstrates the value of engineering capital as a more sophisticated, intersectional and multifaceted conceptualisation of how young people are supported to aspire to engineering trajectories. Further research is warranted to examine patterns of social connection to hobbyist engineers and its relative impact.

This first exploration of knowing a hobbyist engineer also reveals no trends in the hobbies that social connections to young learners engage in. Crosstabulations suggest that those in low, medium and high engineering capital groups report knowing roughly the same distribution of hobbyists who participate in activities relating to areas such as automotive, digital/electronic or woodworking. This suggests that there are limited distinctions of ‘taste’ of hobby and that engineering hobbyists of all types are present throughout society, but it is acknowledged that a larger sample is required to confirm this. Further study should also explore the range of activities that are identified with engineering hobbies: a range of ‘making and fixing’ hobbies were identified suggesting that young learners recognise engineering within various activities (such as culinary applications or textiles).

Whilst a significant positive association is identified between engineering capital and knowing a hobbyist engineer - supporting the inclusion of this subcomponent in future iterations of engineering capital - there is also a clear need for further study to understand this relationship in greater detail. The analysis outlined above should encourage future investigation of hobbyist engineers and the impact of knowing these individuals. Further study may consider the potentially dynamic impact of social proximity to hobbyist engineers.

Familial Capital

A Welch’s one-way ANOVA analysis examined the difference in engineering familial capital scores between engineering capital groups (low, medium, high engineering capital scores). This analysis identified significant differences between groups (F(2, 200.623) = 94.038, p<0.001, ETA^2 = 0.174 with Games-Howell post-hoc testing confirming differences between group mean familial capital scores at all levels (Low: M=-2.08, SD=2.03; Medium: M=-0.50, SD=1.71; High: M=0.98, SD=1.43) (see Appendix H for statistical outputs).

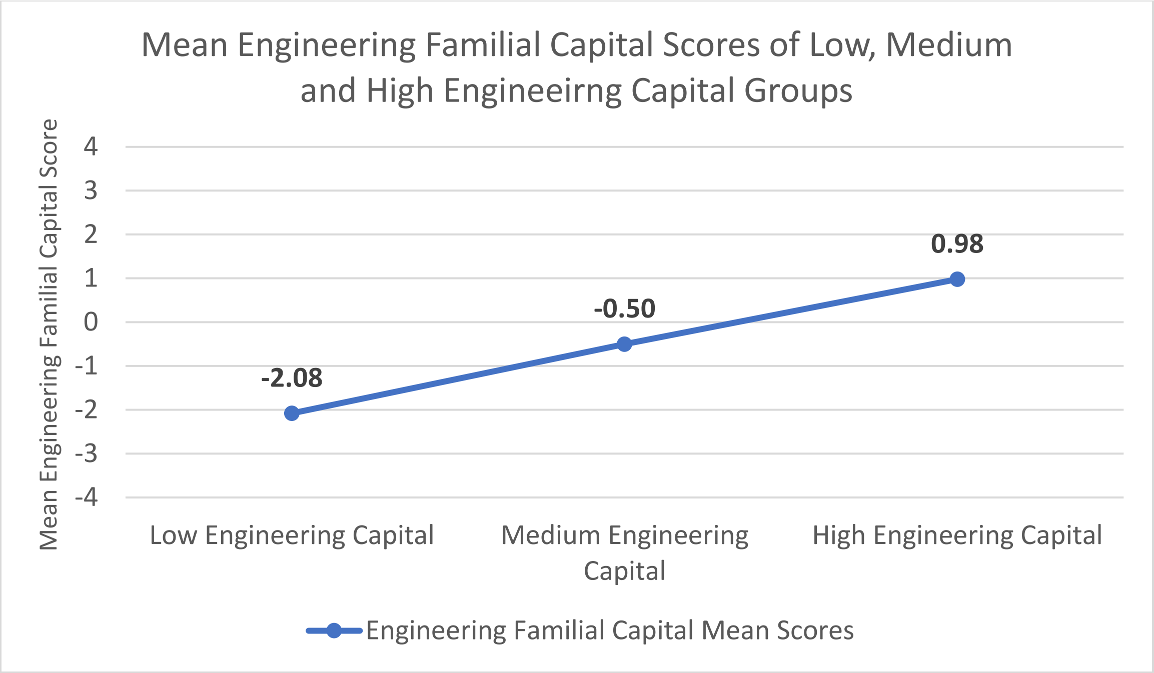

Figure 8.02: Mean engineering familial capital scores of low, medium and high engineering capital groups.

These results demonstrate the expected positive relationship between engineering capital and familial capital for engineering. This supports the relevance of familial capital within an engineering-specific consideration of Bourdieuian capital and the potential use of familial capital in future iterations of engineering capital. The relevance of Yosso's (2005) framing of familial capital suggests that other forms of Bourdieuian capital reimagined within the community cultural wealth framework (such as aspirational capital, navigational capital, or resistant capital) may also offer valuable insight on engineering inequity. The relationship established between familial capital and the engineering capital model further validates the interpretation of the Bourdieuian framework adopted within this thesis as both Yosso and this work challenge the traditional interpretation of Bourdieuian capital with success.

It is noteworthy that this form of engineering capital is relatively scarce: only those in the high engineering capital group report a positive mean familial capital score. This would imply that recognition of engineering within local communities or family histories is poor for the majority of young people. This could be caused by multiple factors. Firstly, it may be that this scarcity is due to the limited geographic sampling of engineering capital within this thesis. Schools from only ten regions were included within this sample which may be insufficient to access geographic regions with a notable engineering community or history. It may be that subsequent samples identify a greater range of engineering familial capital, however the present sample does identify a range of responses which suggest that geographic location is not the only factor in discerning familial capital – as is expected given this subcomponent relates not only to local geographic community but individual family history which is not geographically bound. Second, it may be that this scarcity accurately reflects the scarce supply of familial capital for engineering in the UK context. It may be that relative to the national context only a minority possess a historic communal or familial link to engineering. If this is the case then this scarcity would support its relevance given the importance of scarcity to capital-based models (Bourdieu, 2018). Finally, it may be that the possession of higher rates of engineering capital support the recognition of familial connections to engineering. It may be that those with low or medium levels of engineering capital possess historic family or community connections to engineering, but that the possession of greater levels of engineering capital facilitates greater recognition of their familial link to the engineering domain. This would be consistent with the relationship between capital and causality with the Bourdieuian perspective accounting for both the structured and structuring influence of capital: the capital acts as both effect and cause of inequity (Bourdieu, 2020). If this is the case then interventions to build greater engineering literacy may support greater recognition and access to forms of engineering capital on offer, but unacknowledged, by young learners. These three potential interpretations are not mutually exclusive but support the need to build greater understanding of the concept of familial capital. Future research may adopt a more targeted methodology to compare regions with or without a historic link to engineering or may wish to explore the impact of interventions that reinforce historic links between young learners and their contexts. The statistical significance of engineering familial capital identified within his thesis supports its consideration within future iterations of engineering capital.

Linguistic Capital

Both general linguistic capital (proficiency with languages other than English) and engineering-specific linguistic capital (proficiency with engineering-specific language and communication) were examined in relation to engineering capital groups. Cross-tabulation calculations were applied to compare the general linguistic capital scores of those in low, medium, and high engineering capital groups but found little difference in the general linguistic capital of young learners in these groups. The median responses on the 0-7 general linguistic capital scale were 0 for the low group, and 1 for both the medium and high engineering capital groups. Overall, very little difference was noted between these groups in relation to general linguistic capital which did not warrant further analysis.

However, further analysis of these groups in relation to engineering-specific linguistic capital did identify significant differences. A one-way Welch's ANOVA analysis revealed significant differences in engineering linguistic capital scores (F(2,218.842) = 484.613, $p<0.001$, ETA^2=0.422). Games-Howell post-hoc tests highlighted significant differences at all levels between high (M=1.60, SD= 1.27), medium (M=-0.97, SD= 1.55) and low (M=-3.22, SD= 1.10) engineering capital groups (see Appendix H for statistical outputs).

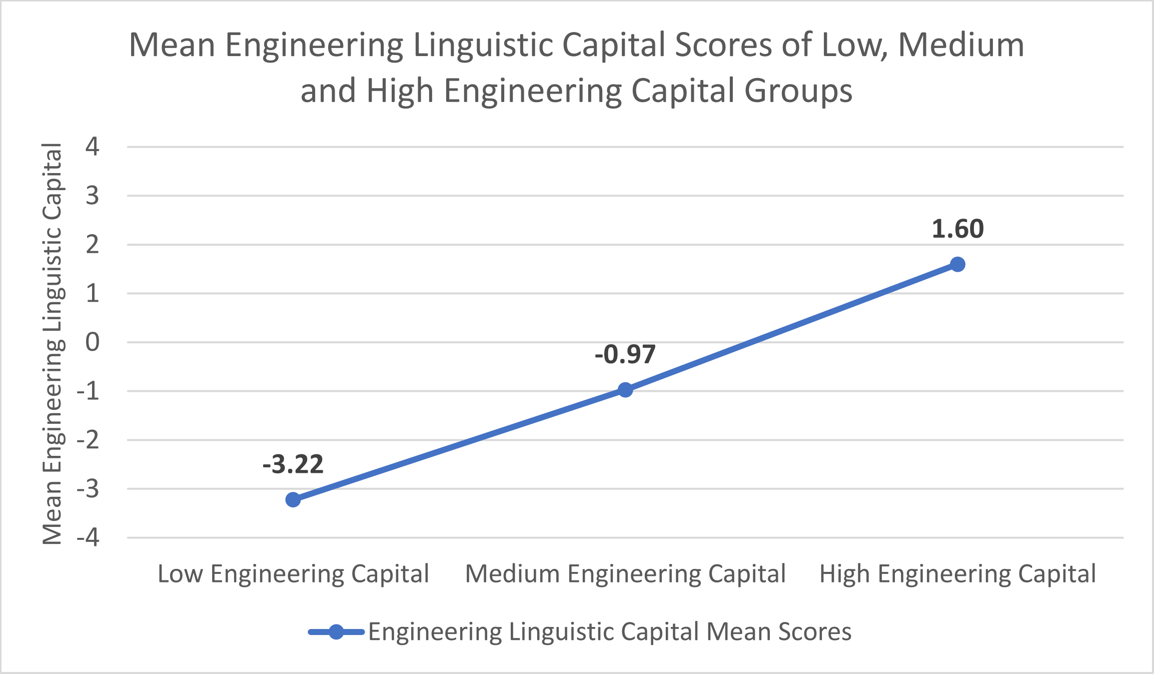

Figure 8.03: Mean engineering linguistic capital scores of high, medium and low engineering capital groups.

The lack of significant differences between engineering capital groups and general linguistic capital is unsurprising given that the domain of engineering does not require a proficiency with a second language. Whilst it may have been relevant to consider the relationship with general linguistic proficiency and ability to engage in the specific linguistic style of the engineering domain these results suggest that this is not the case. These findings would support the approach taken within this thesis to adopt the Bourdieuian framework in a domain-specific, rather than general, manner as results indicate that general linguistic capital is not applicable to the engineering domain. However, a further statistical analysis does identify a significant relationship between engineering capital groups and engineering-specific linguistic capital. Those who possess greater levels of engineering capital report more positive levels of comfort talking about engineering and using technical engineering language. This supports the relevance of this linguistic capital to engineering inequities and the potential inclusion of engineering-specific linguistic capital within future iterations of the engineering capital model. As with familial capital those with a positive linguistic capital for engineering are relatively scarce with only weak positive responses reported by those in high engineering capital groups (M=1.6 of a possible 4). Those with low engineering capital scores on the other hand report very negative mean responses indicating a scarcity to comfort and self-reported ability utilising engineering language (M=-3.22 of a possible -4). This should be expected given the limited presence of engineering within the lives of young learners in the United Kingdom – linguistic capital likely requires an informed source of knowledge or social partner with which a young learner can acquire engineering-specific linguistic capital over time. Engineering linguistic capital is unlikely to be supported in school contexts with a curriculum that features little engineering and low levels of confidence in communicating about engineering amongst UK teachers (EngineeringUK, 2020). It might therefore be expected that those who possess engineering linguistic capital also consume engineering media or know an engineering individual - both of which are indicated by a possession of engineering capital. This warrants further investigation to comprehend the cross-cutting relationship between engineering linguistic capital, its acquisition and other forms of engineering capital. This first examination of engineering-specific linguistic capital would support its relevance to future iterations of engineering capital.

Engineering Engagement

A one-way ANOVA analysis examined the engineering engagement scores of engineering capital groups (low, medium, high engineering capital). This analysis identified statistically significant differences in engineering engagement scores ($F(2,918) = 298.204$, $p<0.001$, $ETA^2=0.394$). Tukey post-hoc testing revealed significant differences at all levels between the mean engagement scores of low (M=-9.31, SD= 7.17), medium (M=0.81, SD=7.58), and high engineering capital groups (M=13.88, SD=6.80). The ETA^2 effect size indicates a very large effect of engineering capital in distinguishing engineering engagement scores (see Appendix H for statistical outputs).

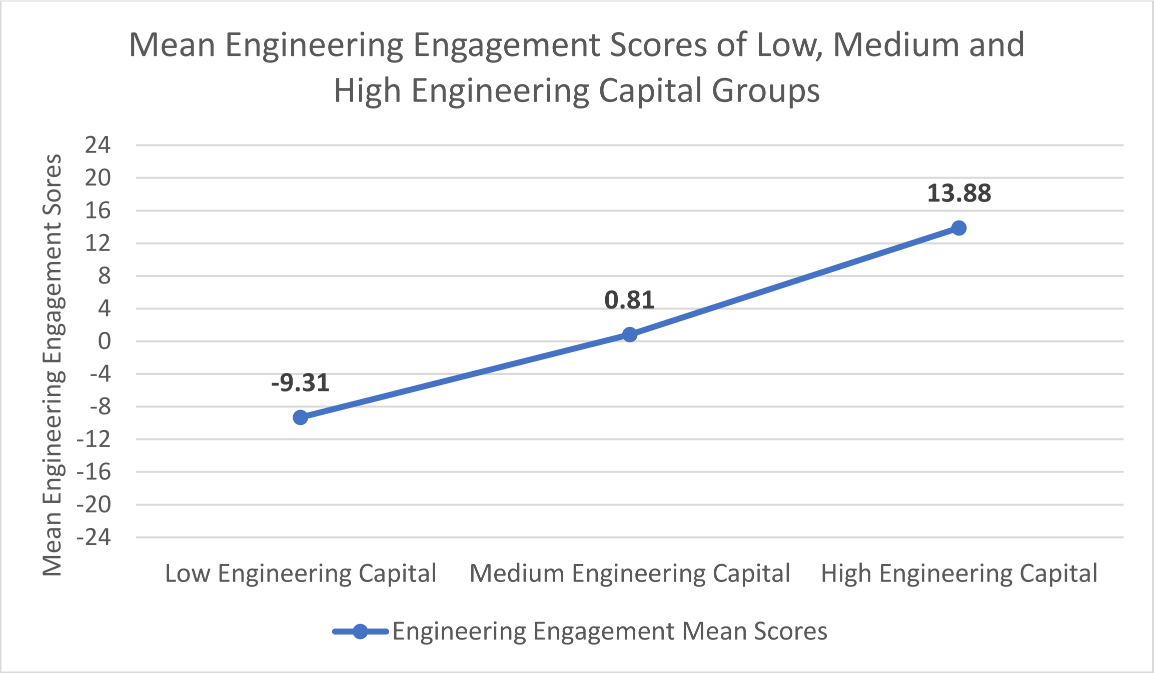

Figure 8.04: Mean engineering engagement scores of high, medium and low engineering capital groups.

This test was adopted to determine whether engineering capital possessed a wider utility beyond understanding engineering aspirational inequities, in particular in its potential relationship to learner engagement and therefore learning and classroom experiences. The results of this analysis indicate that engineering capital is very strongly associated with engineering engagement with statistically significant differences between the engineering engagement scores of engineering capital groups. Those who possess greater engineering capital also possessed greater engineering engagement scores indicating the expected positive association between the possession of capital and affective and cognitive engagement within a domain. These findings support that an aggregated measurement of engagement factors such as self-efficacy, self-concept, valuing of engineering, persistence, curiosity and outcome expectations are positively associated with the possession of engineering capital. These aspects of engagement are recognised in past literature as deeply significant to learning, including achievement, classroom behaviour and academic decision making (Appleton et al., 2008; Dotterer & Lowe, 2011; Finn & Zimmer, 2012; Hospel et al., 2016; Northey et al., 2018). The positive association between engineering capital and engineering engagement therefore supports the relevance of utilising engineering capital to understand learners and classroom experiences extending the potential applications of engineering capital beyond understanding of aspirations.

The relationship between engineering capital and learning contexts further supports the value of engineering capital as a tool to address inequity. Engineering inequities are noted to occur in pre-tertiary education with those in secondary school settings reporting inequitable interest and aspiration in engineering (Hutchinson & Bentley, 2011) and some indications of inequity in primary school settings (Silver & Rushton, 2008). These findings reinforce not only how dominant engineering inequities are throughout UK culture but also the necessity for perspectives on engineering inequity to be compatible with younger audiences and their learning experiences. Engineering capital is supported as relevant to these contexts by the significant association with learner engagement with engineering. Whilst the focus of this thesis has explored the future trajectories of young learners these findings demonstrate the relevance of engineering capital as a lens on present learning experiences. Further study should explore the relationship between engineering capital and classroom experiences including behaviour, achievement and decision making.

The significant association between engineering capital and engineering learning engagement supports the use of engineering capital to understand patterns of decision making for engineering beyond the educational and career decision making established in earlier chapters. Learner engagement is recognised as influential in decision making, persistence and interest for educational experiences. Engagement is not only relevant in relation to formal learning but may also apply to informal or home environment decision making. In this way these findings support the application of engineering capital beyond formal educational and career trajectories to less consequential everyday decision making and alignment to engineering. Engineering capital may therefore assist in understanding how young learners develop over time and in every day circumstances – this would support that engineering capital can be applied at any time as a measure of development towards engineering and not strictly in relation to tertiary educational trajectories or career paths.

The relationship between engineering capital and learner engagement would also support the implementation of engineering capital in an evaluative capacity to frame the impact of interventions that target inequities. Interventions are by nature concerned with change and are designed with objectives and indicators to judge their success. The characteristics included in the engineering learning engagement measure such as self-efficacy, attitudes, and curiosity can feature as objectives of interventions. The significant association between engineering capital and these evaluative indicators support the use of engineering capital to better understand samples and the conditions in which interventions operate. The malleability of these indictors is consistent with the view of Bourdieuian capital taken within this thesis supporting the compatibility of these considerations. Some interpretations of Bourdieuian capital would question the malleability with which engineering capital may change, however within this thesis Bourdieuian capital is acknowledged as an evolving and changeable characteristic that can be developed over time (Bourdieu & Passeron, 1977). The changeability of engineering capital and its significant positive association with engineering engagement would suggest that interventions to address engineering capital are possible. Whilst gender or social class conditions are fixed or resistant to change engineering capital may represent a framing of inequity that is compatible with targeted support for meaningful change in engineering inequities. Further study is warranted to examine the degree to which engineering capital can be supported to develop through intervention strategies.

The positive relationship between engineering capital and engineering engagement supports that engineering capital holds value in applications beyond that of understanding aspirations to future engineering trajectories. The strong positive link between learning engagement and engineering capital indicates that engineering capital may apply to understanding learners and learning experiences. Future iterations of engineering capital should explore this further to establish the wider utility of engineering capital in classroom and wider learning contexts.

Conclusions

The engineering capital model developed within this thesis has been validated as an effective lens on engineering inequity but should be recognised as only one possible interpretation of Bourdieuian capital within the engineering domain. Though novel and more sophisticated than previous approaches to understanding capital in the engineering domain future research and development may iterate this model to ensure its continuing relevance or improve on its effectiveness. In this chapter this process of iteration was supported by the examination of four further potential subcomponents of engineering capital and one further application of this model to widen its scope of utility. All four further subcomponents – two revisited and two new forms of capital – examined within this chapter are found to be significantly aligned to engineering capital. Those who possess greater values of engineering capital also possess greater levels of these further forms of engineering-specific resource. The four further subcomponents demonstrate an evolution in the forms of capital considered within the engineering capital model developed in Chapters Five, Six and Seven. The re-examination of existing subcomponents ('engineering literacy' and 'knowing an engineer') provides an opportunity to challenge the interpretation of cultural and social capitals included within the model: this recognises the complexity of the Bourdieuian framework and its application but supports the validity of the developed model. The introduction of new subcomponents ('familial capital' and 'linguistic capital') incorporates wider interpretations of Bourdieuian thinking, such as Yosso's Community Cultural Wealth model, to develop the rigour and scope of the underlying conceptual framework of the engineering capital model.

The significant alignment of these four further subcomponents with the engineering capital model demonstrates two key findings. First, it demonstrates that the engineering capital model developed in this thesis is only one possible model of capital for engineering. Alternative interpretations of Bourdieuian capital may be relevant and other researchers may draw on this framework differently to examine engineering inequities. And second, despite the first point, these findings support that the engineering capital model developed in this thesis is generally representative of engineering capital overall with possession of all four further forms of capital found to be consistent with the possession of engineering capital as framed within the developed model. This validates the engineering capital model developed in this thesis and supports its utility in investigating and understanding engineering inequity.

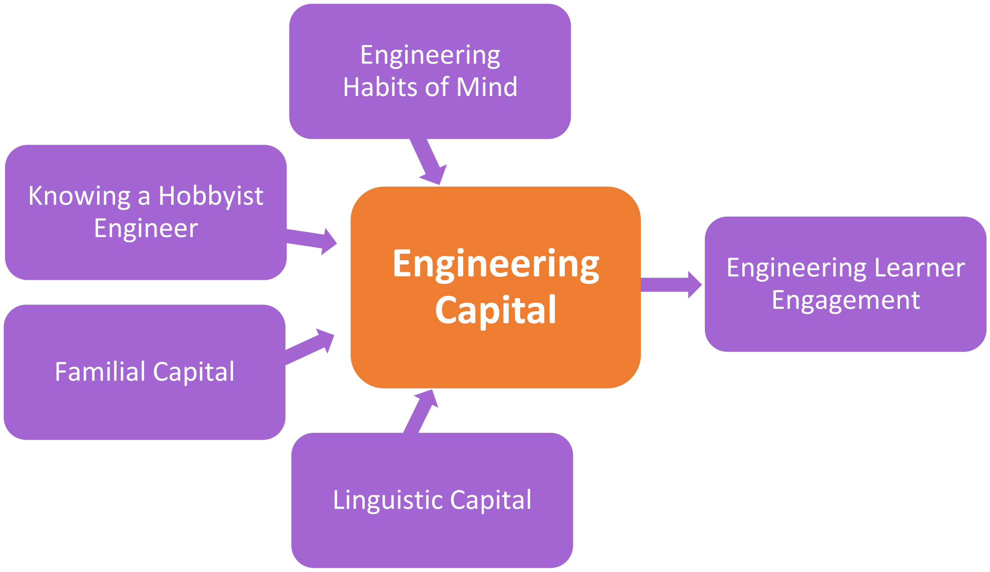

Figure 8.05: Further dimensions considered in relation to the engineering capital model of inequity.

The examination of these further forms of capital also identify differing levels of scarcity and possession of capitals for engineering that warrants further investigation. Whilst the engineering capital model is an aggregate structure the examinations within this chapter also recognise the importance of investigating individual forms of capital to better understand their specific prevalence and impact on engineering inequities. The iterative examination of engineering capital in this thesis also recognised a significant relationship between the possession of engineering capital and affective and cognitive learning engagement with the engineering domain. These findings highlight the usefulness of applying engineering capital to a further purpose of understanding engineering learner readiness and experiences. This widens the scope of application of this model beyond aspirational inequity to also consider current experiences of future engineers. Overall, the association qualifies the application of engineering capital within school settings to inform learner readiness for engineering and support evaluative efforts in addressing inequity.

These further dimensions of engineering capital not only offer insight as to how future iterations of engineering capital may be improved upon, but also highlight avenues of further research to explore engineering inequities in the UK context. If the formative engineering capital model is understood as a synthesis of past literature through a novel Bourdieuian framework then these five dimensions might be understood as new lines of enquiry that may offer insight to the challenges of engineering inequity in the UK. Iteration must be approached carefully as modifications to models or instruments may lower the effectiveness of these tools, however such iterations may still offer novel insights to guide greater understanding. In this way the iterative process is also a call for further knowledge development and novel application and therefore should be strongly supported.

Overall, these findings are optimistic for the domain of engineering capital and reinforce the benefits on offer by this perspective. These findings highlight future avenues of research to examine engineering inequities in the UK and wider application of the engineering capital model to understand learners and learning behaviour alongside support for the next generation of UK engineers.

CONCLUSIONS

Thesis Objective

This thesis set out to develop a greater understanding of the long-standing engineering inequities present within the United Kingdom. These entrenched patterns of access, participation, success and representation within the engineering domain were positioned as damaging to the social justice and economic prosperity of the nation. Current understanding of these inequities was criticised as lacking depth, an engineering-specific focus, and practical value to inform successful intervention strategies. A particular need to better understand the experiences of young people was identified to better support future generations of engineers. The objective of this thesis set out to address this issue by developing a more sophisticated understanding of engineering inequities amongst young learners in the UK.

Key Findings

A novel perspective on engineering inequity challenges in the United Kingdom

A detailed review of past literature produced a cross-cutting examination of engineering inequities in the UK context, synthesising historic, economic, cultural and educational perspectives. Engineering inequities were found to be ubiquitous, manifesting in many forms and contexts. A complex relationship was acknowledged between contemporary society and the engineering domain with dated conceptualisations of engineering still present within the public consciousness. This analysis thereby offered a cultural hypothesis to explain the lingering inequities of engineering, positioning inequities as ubiquitous and deeply rooted within the UK context. This further supported the need for a novel approach to understanding engineering inequities that moved beyond immediate or imminent challenges to acknowledge the enduring cultural and social influences that shape (and will continue to shape) the engineering domain. This framing of engineering offers a novel interpretation of engineering skill shortage and social justice challenges currently active within the UK context.

Science capital was not found to apply to the engineering domain

Science capital, Archer et al.’s (2015) innovative science inequity model, was adopted within this thesis as a potentially valid lens to develop greater understanding of engineering inequities. Despite its popularity relatively little past research has critically examined this body of literature. A novel theoretical critique of science capital supported its validity as a perspective on science inequity but challenged the notion –

adopted by some stakeholders – that science capital may apply to other STEM domains. The forms of cultural and social capital included in this model were found to theoretically differ in their relation to science or engineering. A further empirical application with 921 secondary school-aged learners confirmed this, finding that the science capital instrument could not accurately identify more than 1% of young learners who wished to study or work in engineering in the future. Though not a predictive model, this lack of utility for understanding the future aspirations of young people highlights the limited value of applying science capital to the engineering domain. This further supports the position adopted within this thesis that engineering inequities require engineering-specific solutions. These findings offer unique insights as to the utility and scope of the science capital model as a dominant body of thought within the study and intervention of STEM inequities.

An engineering-specific model of capital was found to be valuable

Whilst the science capital model and instrument were found to lack a relevance to the engineering domain this analysis did validate the underlying domain-specific Bourdieuian capital framework as of value to the study of engineering inequity. An 'Archer-style engineering capital' instrument was developed through the translation of the science capital empirical tool to measure the capitals for engineering possessed by young learners. This engineering-specific instrument outperformed the science capital model in examinations of engineering inequity empirically establishing the relevance of the Bourdieuian framework to the engineering domain. Very little past research has explored engineering inequity from a Bourdieuian perspective highlighting the novelty of this approach. The 'Archer-style engineering capital' instrument was recognised as focusing on the forms of capital most relevant for science, not engineering, supporting the need to develop a 'true' engineering-specific capital model. This investigation demonstrated the value offered by the Bourdieuian perspective and validated the adoption of this framework to develop a greater understanding of the engineering inequities facing the UK. The scope of this Bourdieuian perspective was consistent with the acknowledged culturally rooted nature of engineering inequity supporting the use of this theoretical perspective to develop a richer comprehension of the engineering domain.

New domain-specific models of capital can be developed from Archer et al.'s approach

The instrument development methodology adopted by Archer et al. (2015) to develop the domain-specific model of science capital was critically considered in relation to wider instrument development approaches. This outlined the process through which a domain-specific model of capital could be developed in line with best practices of instrument development – something that was not explicitly focused on in formative science capital literature. Little or no literature had considered the science capital publications as a guide to domain-specific capital model development or replicated this process to validate its utility. The analysis of this process and the outlining of its second successful adoption within this thesis represents a novel output as a guide to the creation of domain-specific models of Bourdieuian capital. Given the success of science capital, and that of the engineering capital model offered by this thesis, this outline may support future researchers to develop their own domain-specific applications of Bourdieuian capital to better understand and combat inequities.

An engineering capital model offers a valuable lens on engineering inequity

The engineering capital model developed within this thesis, drawing on the methodology first applied by Archer et al. (2015), has been found to be a valid perspective on engineering inequity. Young learners who aspire to engineering pathways possess significantly greater engineering capital than peers who do not, the distribution of engineering capital is found to align with widely acknowledged gender and social class inequities in engineering, and the model is found to be significantly predictive of aspirations to engineering education and careers. This model has been validated as a useful lens on engineering inequity and offers both a theoretical and empirical utility in understanding and addressing inequity. The engineering capital lens not only aligns with past understandings of inequity but offers novel insights acknowledging intersectionality and the currently limited understanding of how young learners are supported to become engineers. With this tool it is possible to better understand groups and individuals and their trajectories towards future engineering roles. Current approaches to framing inequity, such as descriptive percentage reports of how many engineering roles are filled by certain groups, are criticised in this thesis as lacking utility and depth. The engineering capital perspective can address this lack of understanding by developing more sophisticated understandings of support for future engineers beyond characteristics such as gender or social class that are not capable of being directly intervened with. Cultural capital, social capital and behaviours and practices for engineering, on the other hand, can be intervened with to support future engineers. In this way the model of engineering capital is a proactive perspective on inequity that can accomplish the objective of this thesis to develop deeper and more practical understanding of access, participation, success and representations in the engineering domain to support greater social justice and economic resilience within the engineering domain.

The developed engineering capital instrument has wide applications

The engineering capital model was also found to positively align with other subsequently examined forms of engineering capital not included within this first iteration of the engineering capital model. This suggests that the developed model of engineering capital is representative of wider resources not considered within its structure, supporting its scope as a broadly useful lens on inequities. This further analysis of engineering capital also identified a strong significant relationship between engineering capital and engineering learner engagement: those who possessed greater capital also possessed affective and cognitive engagement characteristics that are indicative of meaningful learning. The positive association demonstrates a wider application of engineering capital as a perspective on learners and learning experiences. Although designed to understand inequities within engineering trajectories these findings demonstrate wider applications of the developed model and instrument. Engineering capital could be adopted to better understand pupils and their relationship with learning for engineering. This widens the scope of application to schools and classrooms and supports the use of this model to build greater comprehension of the relationship between learning experience and future trajectories. These findings also suggest that engineering capital may be applied in an evaluative function to directly intervene with inequity and support learning.

Meeting the Thesis Objective

The objective of this thesis set out to develop a greater understanding of engineering inequities to inform practical change to better support the next generations of UK engineers. This objective has been met through the development of the engineering capital theoretical model and empirical instrument. The theoretical model of engineering capital allows inequities to be conceptualised in a more nuanced manner that goes beyond simplistic group differences based on gender, ethnicity or social class. This approach recognises the intersectionality of inequity and the multitude of factors that can shape patterns of access, participation, success and representation in the engineering domain. The engineering capital instrument similarly supports the development of understanding and intervention. With this concise instrument it is possible to rapidly assess an individual’s relationship to resources for engineering that are strongly associated with current learning and future trajectories for engineering. This offers the ability to better understand individuals and groups in a comparable, validated, data-led fashion. Through the use of this tool engineering inequities can be better understood throughout the UK. The forms of capital included in the model and instrument of engineering capital are theorised to be malleable and responsive to intervention. This perspective therefore supports the development of interventions to challenge entrenched engineering inequities.

The development and validation of the engineering capital perspective therefore represents the successful accomplishment of the thesis objectives to develop greater understanding of engineering inequities in the United Kingdom.

Research Limitations

Whilst the thesis was successful in its objective the project was not without its limitations. The sample recruited to explore engineering inequities was limited (N=921) in relation to the overall population of young learners and so cannot be considered to be representative. The underlying conceptual framework of Bourdieuian capital adopted within this thesis recognises the key influence of cultural and societal context – aspects shared across many settings within a nation – that would support the validity of a non-representative sample. However, this thesis also recognises that engineering inequities are nuanced and as a result it should be expected that individual differences are present within the population in relation to patterns of engineering inequity. Whilst the sample featured in this thesis is of considerable size a larger sample is necessary to further reinforce the validity of the findings for the wider UK context. The sample also lacked representation for some groups, with a particular issue around the representation of individuals from black and minority ethnic (BAME) groups. These limitations were in part due to the challenge of collecting data during a period of Covid-19 interruption. Further sampling and investigation with the engineering capital instrument is warranted to continue its process of validation – these efforts should take care to include a more representative sample to confirm the wider utility of the developed model and instrument.

The Covid-19 pandemic also impacted the ability to conduct in-person data collection in schools, which limited the range of research methods available within this project. The quantitative-dominant questionnaire methodology applied within this thesis provided the opportunity to collect a larger volume of data but also introduced limitations to the depth of data it was possible to collect as well as the capacity to follow emerging lines of enquiry within educational contexts. Qualitative approaches such as focus groups or interviews with teachers, parents and learners would have provided a deeper dataset from which to reflect on engineering inequities. Targeted interviews with those who possessed higher or lower levels of engineering capital would have been particularly insightful and may have guided future avenues of research that could not emerge within the confines of a quantitative methodology. This lack of triangulation limits the dimensions of insight offered by this thesis and should be approached in future study.

Future Research

Having developed the engineering capital model and instrument within this thesis project it is next necessary to apply this perspective widely to robustly understand engineering inequities within the United Kingdom. The initial formation and application of the engineering capital lens outlined in this thesis is suggestive and informative but requires further investigation with larger samples of young learners. The concise nature of the engineering capital instrument supports the ease of its application to new samples. The collection of data from secondary schools across the UK would develop a sample of thousands of young learners with relatively little investment of time and effort on the part of schools. Such an approach could further validate the relevance of the engineering capital instrument – particularly with groups that were under-represented within this thesis sample – whilst also developing a richer understanding of how young people in the UK are supported to become engineers. Such an application would provide the opportunity to develop the engineering capital model through iteration and exploration of novel forms of resource.

Future research would also benefit from the adoption of qualitative methods to triangulate and advance understanding of engineering inequities amongst young learners. Aspirations and trajectories are acknowledged as deeply complex constructs and, whilst the engineering capital model can comprehend and predict these reasonably well, qualitative methods may unearth nuances that quantitative methods cannot access. This would also serve to develop richer contacts with schools and support the introduction of the engineering capital instrument to new samples whilst supporting the further development of the engineering capital perspective. Whilst the engineering capital instrument was designed to be an efficient quantitative tool further qualitative research concerning the possession of and nuance within engineering capital may inform improvements to future iterations of the instrument.

Although this thesis data collection focused on secondary school-aged learners the Bourdieuian perspective notably applies to any age group, implying that the engineering capital perspective may support greater understanding of a range of engineering inequities. Engineering capital may offer a valid lens on the experiences of those in vocational and academic further education pathways or assist in understanding the performance of engineering university students. A simplified engineering capital perspective may also function as a valid lens on the formative engineering experiences of primary school-aged learners. Applying the engineering capital lens to primary school-aged samples would require the underlying Bourdieuian framework of this model to be revisited. For example, primary-aged learners are likely still developing their ‘primary habitus’ and so may be more flexible to intervention in shaping engineering trajectory. Bourdieuian theory would also recognise the significant influence of parental gatekeepers on young learners which may support the investigation of engineering capital within home contexts or family units rather than the capital of individual learners. Future research should explore the potential for such wider applications of the engineering capital perspective.

A further line of enquiry may revisit the 'deficit' thinking inherent to a Bourdieuian perspective on inequity and explore forms of capital that may support engineering aspirations but are distinct from those possessed by the dominant social group recognised as 'engineers'. This may involve exploring forms of resistant capital that develop amongst non-engineering groups to combat engineering inequities and support aspirations, in line with the work of Yosso and others who have considered the advantageous capital of 'non-dominant' groups. In an engineering context this may involve exploring the engineering capital of those who approached engineering careers through non-typical pathways or come from marginalised groups. It may also involve an exploration of the forms of capital held by those in engineering-related or adjacent roles.

Acknowledging the practical need to address inequities, future research may also adopt an experimental paradigm drawing on the contents of the theoretical model of engineering capital to design interventions to address inequities. Each aspect of the model is theoretically malleable to change – pedagogical structures, novel experiences or curricular redesign may offer the opportunity to develop engineering capital to support young learners to place themselves on engineering trajectories. For example, the engineering capital perspective may inform STEM outreach programmes that support the development of particular forms of cultural or social capital for engineering. Experimental research methodologies may collect data at multiple time points during this outreach programme to track changes in aspiration over time as engineering capital is developed to provide a greater understanding of the process through which capital is accumulated by learners. Another intervention may utilise the engineering capital lens to inform teacher training for engineering or support the provision of guidance and curricular-mapped engineering learning experiences that could be adopted to combat engineering inequity. As a tool focused on improving understanding it would be possible to draw on and apply the engineering capital perspective in many contexts to support a greater comprehension of engineering inequities and support meaningful intervention against social injustices and national economic challenges in the engineering context.

At its core, the issue of engineering inequity and its resulting challenges (such as social injustice or insufficient skills supply) stem from a need for change to support the engineering domain. This thesis has successfully supported this drive for change through the development of more detailed and useful insights into engineering inequities in the United Kingdom. Future efforts may be informed by the engineering capital lens to build greater resilience and equity within the UK engineering domain.

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APPENDICES

V1.0, Date: 30/07/2020
Your pupils are invited to participate in a research study. Before you decide if you wish for your pupils to take part in this study it is important that you understand why the research is being done and what it will involve. Please read the following and decide whether you want to continue.

Study title: Exploring Science and Engineering among UK School-Age Young People

What is the purpose of the study?
This research project is exploring what attitudes young people in UK have about science and engineering. We want to learn what sort of opinions your pupils have about these subjects and also explore some characteristics they have that might affect their attitudes about science and engineering. This includes questions about things like who they might talk to about science or engineering, what sort of hobbies and interests they have, what sort of job would they be interested in having in the future. Answering these questions allows us to better understand how young people think about and experience science and engineering in their lives which in turn helps us understand how to teach these subjects.

Why have I/they been invited to take part?
You have been chosen to participate in this study because you are an education provider teaching secondary school aged pupils in the UK. We will be asking hundreds of Year 7 – 11 pupils from across the UK to take part in this project.

Do I/they have to take part?
Please note: you or your pupils do not have to participate unless you want to. This study is completely voluntary. They can decide they do not wish to complete the questionnaire at any point and stop, or they can choose not to submit their data at the end of the questionnaire.
The questionnaire data will be examined anonymously. Pupils will be asked to describe their gender, ethnicity, postcode, year group and name your school but we will not attempt to identify them from this information. As the data will be collected anonymously and not attached to an individual pupil's name it will be impossible to identify and remove their data after they have chosen to submit it.

What will happen if I/they take part?
If you and your pupils agree to take part in the research study they will be asked to complete a questionnaire answering questions about their opinions and experiences with science and engineering and some questions about their life and family background. Once they are finished they will be asked if they wish to submit this data to us. Preferably this would be online via our digital questionnaire, but physical copies can be sourced if necessary in which case postage would be provided to return send these to the University. Each pupil only needs to fill in the questionnaire once. The teacher will decide when the pupil will be asked to do this task – preferably in class time however it can also be completed as a homework activity. A questionnaire will be provided to you for your information.
How will their data be used?

Pupil questionnaire answers will be combined with the answers from all our participants from across the UK and then analysed as a whole so that we can better understand how young people in the UK think about and experience science and engineering in their lives. This may feed into further examinations in future research.

The University processes personal data as part of its research and teaching activities in accordance with the lawful basis of 'public task', and in accordance with the University's purpose of "advancing education, learning and research for the public benefit".
Under UK data protection legislation, the University acts as the Data Controller for personal data collected as part of the University's research. The University privacy notice for research participants can be found on the attached link https://www.uclan.ac.uk/data_protection/privacy-notice-research-participants.php
Further information on how your data will be used can be found in the table below.

How will data be collected?	*By questionnaire*
How will data be stored?	*Data will be collected via an online survey tool. Digital data will be moved and stored on a password protected account and password protected file for analysis. Physical data will be returned anonymously and stored in a locked drawer until digitised.*
How long will data be stored for?	*Data will be stored for the duration of the development and refinement of this work.*
What measures are in place to protect the security and confidentiality of data?	*Digital data will be collected via a password protected questionnaire tool, stored in a password protected file on a password protected account.* *Physical data will be returned via post.*
Will data be anonymised?	*Yes, all data is anonymous from the point of collection.*
How will data be used?	*Pupils will be asked questions that describe them including year group, school name, ethnicity, home post code. They will be asked questions about their attitudes and experiences with science and engineering. They will also be asked to describe themselves and their family background.* *Collecting this data allows us to understand what their attitudes and experiences with science and engineering are, and then examine patterns in these for people from different backgrounds. This will allow us to better create more effective ways of examining how science and engineering are considered and taught.*

Who will have access to data?	*The only people with access to pupil data will be the research team – consisting of three researchers. One researcher will be responsible for anonymising all data.*
Will data be archived for use in other research projects in the future?	*Yes, this will be archived for further development and refinement of the research work and outputs.*
How will data be destroyed?	*Once of no use this data will be destroyed through secure deletion, shredding.*

Are there any risks to taking part?
There are no risks involved in participating with this study. Questions are not provocative or controversial. Should pupils feel uncomfortable with participating at any point they are free to cease participation and withdraw from the study.

Are there any benefits to taking part?
There are no likely benefits to participating in this study; no financial incentive is offered. However, participation will assist in the development of knowledge and allow science and engineering education to be approached with greater confidence.

What will happen to the results of the study?
The results of this study will be published in academic publications and disseminated at conferences and other professional events. The results will primarily feature in a thesis dissertation exploring science and engineering attitudes in the UK. Schools and pupils will not be identifiable in any published results of the study.

What will happen if they want to stop taking part?
Pupil data will only be included within the study if you consent their participation and they wish to participate and submit their data at the end of the questionnaire. This means they are free to withdraw and stop participating in the study at any time, for any reason, and do not need to explain why.
As this data will be anonymous at point of collection we will not be able to identify their individual data once it has been submitted. This means that we will not be able to remove their data from the study after they have submitted it to us.

What if they are unhappy or if there is a problem?
If you or they are unhappy, or if there is a problem, please feel free to let us know by contacting Richard Davies (RDavies15@uclan.ac.uk) and we will try to help. If you remain unhappy, or have a complaint which you feel you cannot come to us with, then please contact the Research Governance Unit at OfficerForEthics@uclan.ac.uk.
The University strives to maintain the highest standards of rigour in the processing of your data. However, if you have any concerns about the way in which the University processes your personal data, it is important that you are aware of your right to lodge a complaint with the Information Commissioner's Office by calling 0303 123 1113.

Who can I contact with further questions?
Rory McDonald, University of Central Lancashire, RAMcDonald5@uclan.ac.uk
Dr Richard Davies, University of Central Lancashire, RDavies15@uclan.ac.uk

SCHOOL GATEKEEPER CONSENT FORM

Version number and date: V1.0, 30/07/20
Research ethics approval number:

Exploring Science and Engineering among UK School-Age Young People

Name of researchers: Dr Richard Davies, Dr Liz Granger, Rory McDonald

Please initial in each box if you agree with the statement. Participation will only proceed if all boxes are initialed.

	Initial
I confirm that I have read and have understood the information sheet dated 30/07/20 for the above study, or it has been read to me. I have had the opportunity to consider the information, ask questions and have had these answered satisfactorily.	
I understand that my pupils taking part in the study involves them filling in a questionnaire.	
I understand that each pupil's participation is voluntary and that they are free to stop taking part and can withdraw from the study at any time without giving any reason and without their rights being affected up until submission of data. However, after they have submitted their anonymous data it will be impossible to later identify them to remove it. In addition, I understand that they are free to decline to answer any particular question or questions.	
I understand that I am consenting to the participation of my pupils 'in loco parentis' and that this complies with local approval processes	
I understand that the information my pupils provide will be held securely and in line with data protection requirements at the University of Central Lancashire	
I understand that confidentiality and anonymity will be maintained and it will not be possible to identify either the educational institution or any individual student in any reports, presentations or publications arising from the research.	

Your name:	
Your school name:	
Your school role:	
Date:	
Signed:	

University of Central Lancashire

V1.0, Date: 30/07/2020

You are invited to take part in a research study. Before you decide if you want to take part there are a few important things for you to know.

Study title: Exploring Science and Engineering Among UK School-Age Young People

What is the purpose of the study?

We want to learn about what young people in the UK think about science and engineering and things about you that might shape your science and engineering ideas. This means asking you about things like who you might talk to about science or engineering, what sort of hobbies and interests you have, what sort of job you would like to have in the future. You answering these questions helps us to understand how young people think about science and engineering and helps us to teach these subjects.

Why have I been invited to take part?

We are asking you to take part because you are a secondary school student in the UK. We are asking hundreds of pupils like you from across the UK to take part.

Do I have to take part?

<u>You do not have to take part unless you want to</u>. This study is completely voluntary. You can decide you do not want to complete the questionnaire at any time and stop, or you can decide not to submit your answers after you have finished.

The answers you give will be examined anonymously. This means your name will not be attached to any of your data. You will not be identified in any analysis or publication. If you submit your data at the end we will have no way of knowing who sent it to us, so you will not be identified from it.

What will happen if I take part?

If you want to take part you will be asked to fill in a questionnaire. Your teacher will decide when this will happen. You only need to fill it in once. You will be asked about your life, your thoughts and experiences with science, and interest in exploring these subjects in the future. This should take roughly 30 minutes to complete.

How will my data be used?

Your answers will be combined with answers from students across the UK then examined as a whole for patterns in how people see and experience science and engineering. This might feed into further research studies in the future.

Your teacher will not see your answers – they will only be seen by the researchers conducting this research and this information will be anonymous and not attached to your name.

This research is being run by staff at the University of Central Lancashire. The University processes personal data as part of its research and teaching activities in accordance with the lawful basis of ‘public task’, and in accordance with the University’s purpose of “advancing education, learning and research for the public benefit”.

Any data you provide will be treated in line with data protection laws, and you can read more about this at the following link: https://www.uclan.ac.uk/data_protection/privacy-notice-research-participants.php

Are there any risks to taking part?
There are no risks involved in taking part, but if you feel uncomfortable at any point you can stop.

Are there any benefits to taking part?
There are no likely benefits to taking part but taking part will help us to development knowledge and understanding about science and engineering.

What will happen to the results of the study?
The results of this study will be written up and published, but you will not be identified in these.

What will happen if I want to stop taking part?
Your answers will only be included in the study if you agree to submit them at the end of the questionnaire.
After you have submitted your answers we cannot go back and remove them later if you decide you do not want to be involved because we aren't attaching your name to your answers.

What if I am unhappy or if there is a problem?
If you are unhappy or if there is a problem please feel free to let us know by contacting Richard Davies (RDavies15@uclan.ac.uk) and we will try to help. You could also speak to your teacher about this. If you remain unhappy or have a complaint which you feel you cannot come to us with, then please contact the Research Governance Unit at OfficerForEthics@uclan.ac.uk.
The University strives to maintain the highest standards of rigour in the processing of your data. However, if you have any concerns about the way in which the University processes your personal data, it is important that you are aware of your right to lodge a complaint with the Information Commissioner's Office by calling 0303 123 1113.

Who can I contact with further questions?
Rory McDonald, University of Central Lancashire, RAMcDonald5@uclan.ac.uk
Dr Richard Davies, University of Central Lancashire, RDavies15@uclan.ac.uk

DEBRIEF

Thank you for taking part in this study. Taking part will help us to better understand how young people in the UK see and experience science and engineering and help us understand how to teach these subjects. Your answers will be combined with all the answers we collect from students like you in the UK and then looked at to find patterns. We will talk about what we have learned in reports and share our findings with others but you will not be identified. Because your name is not attached to your data we cannot remove it now that it has been submitted.

If you have any questions please contact:
Rory McDonald, University of Central Lancashire, RAMcDonald5@uclan.ac.uk
Dr Richard Davies, University of Central Lancashire, RDavies15@uclan.ac.uk

IF YOU AGREE TO TAKING PART IN THIS STUDY PLEASE TICK THE BOX:

"I consent to taking part in this questionnaire" ☐

AND BEGIN THE QUESTIONNAIRE.

About you

Are you a girl or a boy? Please tick the relevant box below.

☐ Girl
☐ Boy
☐ Other (Please state): _______________

What year group are you in? Please tick the relevant box below.

☐ Year 7
☐ Year 8
☐ Year 9
☐ Year 10
☐ Year 11

What is the name of your school?

Write your answer here: ____

What is the postcode of your home address? *E.g. SW1 2LW*

Write your answer here: ____

Can you speak or read a language other than English? Please tick the relevant box below.

☐ Yes
☐ No

If you can speak or read a language other than English, what language and how well? Write down the name of the language and tick the appropriate box.

What language?	How well can you speak or read it?		
	☐ I know a little	☐ I know a lot	☐ I am fluent
	☐ I know a little	☐ I know a lot	☐ I am fluent
	☐ I know a little	☐ I know a lot	☐ I am fluent

Which of the following best describes your ethnic origin?

Please tick the box for your ethnic background:	**If you know your ethnic background more specifically, please also tick the relevant box:**
☐ Asian	☐ Indian ☐ Pakistani ☐ Bangladeshi ☐ Other (Please specify): ___________________
☐ White	☐ British (English, Scottish, Welsh, and/or Northern Irish) ☐ Other (Please specify): ___________________
☐ Black	☐ Caribbean ☐ African ☐ Other (Please specify): ___________________
☐ Chinese or East Asian	☐ Chinese ☐ Japanese ☐ Korean ☐ Other (Please specify): ___________________
☐ Middle Eastern	☐ Arabic ☐ Persian ☐ Jewish ☐ Turkish ☐ Kurdish ☐ Other (Please specify): ___________________
☐ Other (including Mixed and multiple ethnic groups)	☐ Asian and Black ☐ Black and White ☐ Asian and White ☐ Other (Please specify): ___________________
☐ Prefer not to say	

About your family and home

Did your mother leave school before age 16?

☐ Yes
☐ No
☐ Don’t know

Did your mother go to university?

☐ Yes
☐ No
☐ Don’t know

Did your father leave school before age 16?

☐ Yes
☐ No
☐ Don’t know

Did your father go to university?

☐ Yes
☐ No
☐ Don’t know

Approximately how many books, including e-books, are there in your home?

☐ None
☐ A few (less than 20)
☐ Many (more than 20, less than 50)
☐ Very many (more than 50, less than 100)
☐ A lot (more than 100)

What do science and engineering mean to you?

When you hear the word “science” what comes to mind? You can select multiple options by ticking boxes below.

☐ Advancement, the future, a better world
☐ Biology, chemistry, physics
☐ Economic benefits, jobs in the sciences
☐ Engineering
☐ Environment, nature, plants, animals
☐ Experiment, inquisitive, understanding
☐ Explosions
☐ Health, drugs, cures for diseases, doctors
☐ Ideas, invention, discover, research
☐ School, exams, lessons, teachers
☐ Social sciences, economics, psychology
☐ Working together
☐ Space, rockets, astronomy
☐ None of these come to mind

Can you think of any science jobs that a university science degree could lead into? List any that quickly come to mind in the box below, but do not spend long on this task.

When you hear the word "engineering" what comes to mind? You can select multiple options by ticking boxes below.

☐ Advancement, the future, a better world
☐ Biology, chemistry, physics
☐ Economic benefits, jobs in engineering
☐ Science
☐ Experiment, inquisitive, understanding
☐ Explosions
☐ Ideas, invention, discover, research
☐ School, exams, lessons, teachers
☐ Working together
☐ Space, rockets, astronomy
☐ Electricity
☐ Mechanics, cars
☐ Airplanes
☐ Bridges, roads, buildings
☐ Building things
☐ Fixing things
☐ Designing things
☐ Solving problems
☐ Using maths in the real world
☐ Computers, programming
☐ Messy work
☐ Using tools
☐ Beings hands on
☐ None of these come to mind

Can you think of any engineering jobs that a university engineering degree could lead into? List any that quickly come to mind in the box below, but do not spend long on this task.

Have you come across engineering in your education so far, and if so where? You can select multiple options below.

☐ In a science class
☐ In a design and technology class
☐ In a maths class
☐ In an engineering class
☐ I have not come across engineering in my education
☐ Other. Please state where: ________________________

You in school

What would you say was your overall grade for the following subjects in your Standard Attainment Tests (SATs) at the end of Year 6? If you were told this score it would have been between 80 and 120. If you cannot remember these or were never told select "Don't know or remember". Please tick the box for the relevant answer below.

	Grade brackets				
	80 to 90	91 to 100	101 to 110	111 to 120	Don’t know or remember
Science	☐	☐	☐	☐	☐
Maths	☐	☐	☐	☐	☐
English	☐	☐	☐	☐	☐

Which of the following statements below is true for you now in each of the following subjects?

	I am in one of the top sets	I am in one of the middle sets	I am in one of the bottom sets	There are no sets in my school
Science	☐	☐	☐	☐
Maths	☐	☐	☐	☐
English	☐	☐	☐	☐

You and your future career

What job would you like to have in the future?

Write your answer here: ____

How much do you agree with the following statements? Please tick the relevant box for each statement below.

	Strongly disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly agree
I would like to have a job that uses science	☐	☐	☐	☐	☐
People who are like me work in science	☐	☐	☐	☐	☐
When I grow up I would like to be a doctor or work in medicine	☐	☐	☐	☐	☐
I want to become a scientist	☐	☐	☐	☐	☐
I would like to have a job that uses engineering	☐	☐	☐	☐	☐
People who are like me work in engineering	☐	☐	☐	☐	☐
I want to become an engineer	☐	☐	☐	☐	☐
Anyone can become an engineer	☐	☐	☐	☐	☐
I would like to have a job that involves designing and making things	☐	☐	☐	☐	☐
I would like to work in an engineering related job, but not in an engineering industry	☐	☐	☐	☐	☐
People who are like me work in jobs designing and making things	☐	☐	☐	☐	☐

How much do you agree with the following statements? Please tick the relevant box for each statement below.

	Strongly disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly agree
A science qualification can help you to get many different types of job	☐	☐	☐	☐	☐
It is important to understand engineering even if you don't want an engineering job in the future	☐	☐	☐	☐	☐
An engineering qualification can help you get many different types of job	☐	☐	☐	☐	☐

Talking to people about science and engineering

When you are not in school how often do you talk about science with other people?

☐ Never or rarely (once a year)
☐ A few times a year
☐ About once a month
☐ About once a week
☐ Almost every day

Who do you talk with about science? You can select multiple options below.

☐ Friends
☐ Directly from scientists
☐ Siblings (brothers or sisters)
☐ Teachers
☐ Parents or guardians
☐ Extended family members (grandparents, aunts, uncles, cousins)
☐ People I know from my community
☐ No one
☐ Other (please state): ____________________

When you are not in school how often do you talk about engineering with other people?

☐ Never or rarely (once a year)
☐ A few times a year
☐ About once a month
☐ About once a week
☐ Almost every day

Who do you talk with about engineering? You can select multiple options below.

☐ Friends
☐ Directly from scientists
☐ Directly from engineers
☐ Siblings (brothers or sisters)
☐ Teachers
☐ Parents or guardians
☐ Extended family members (grandparents, aunts, uncles, cousins)
☐ People I know from my community
☐ No one
☐ Other (please state):____________________

Knowing someone who works in science

Do you know anyone (family, friends, or community) who works as a scientist or in a job that uses science?

☐ Yes ☐ No ☐ Don't know

If you said yes you know someone among your family, friends, or community who works as a scientist or in a job that uses science can you tell us who they are and what job they do?

Who is this person to you? ***e.g. your sister***	**And what is their job?**

Knowing someone who works in engineering

Do you know anyone (family, friends, or community) who works as an engineer or in a job that uses engineering?

☐ Yes ☐ No ☐ Don't know

If you said yes you know someone among your family, friends, or community who works as an engineer or in a job that uses engineering can you tell us who they are and what job they do?

Who is this person to you? ***e.g. your sister***	**And what is their job?**

Knowing someone with a designing and making things hobby

Do you know anyone (family, friends, or community) who has a hobby that involves engineering, e.g. designing and making things, woodworking, crafts, DIY?

☐ Yes ☐ No ☐ Don't know

If you said yes you know someone among your family, friends, or community who has a hobby that involves engineering can you tell us who they are and what hobby they do?

Who is this person to you? ***e.g. your sister***	**And what is their hobby?**

More about your family

How much do you agree with the following statements about your parents? Please tick the relevant box for each statement below.

"One or both of my parents…	Strongly disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly agree
...Sign me up to activities outside of school time (e.g. dance, music, clubs)"	☐	☐	☐	☐	☐
...Expect me to go to university"	☐	☐	☐	☐	☐
...Think science is very interesting"	☐	☐	☐	☐	☐
...Has explained to me that science is useful for my future"	☐	☐	☐	☐	☐
...Think that engineering is very interesting"	☐	☐	☐	☐	☐
...Think it is important for me to learn about engineering"	☐	☐	☐	☐	☐
...Has explained to me that understanding engineering is useful for my future"	☐	☐	☐	☐	☐
...Know a lot about engineering"	☐	☐	☐	☐	☐
...Expect me to study science after my GCSEs"	☐	☐	☐	☐	☐
...Expect me to study maths after my GCSEs"	☐	☐	☐	☐	☐
...Expect me to study engineering after my GCSEs"	☐	☐	☐	☐	☐

Your understanding of science and engineering

How much do you agree with the following statements? Please tick the relevant box for each statement below.

	Strongly disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly agree
Other people think of me as a science person	☐	☐	☐	☐	☐
I know how to use scientific evidence to make an argument	☐	☐	☐	☐	☐
I know quite a lot about science	☐	☐	☐	☐	☐
I am confident about giving answers in science lessons	☐	☐	☐	☐	☐
Other people think of me as an engineering-type person	☐	☐	☐	☐	☐
I know how to design and make things	☐	☐	☐	☐	☐
I know quite a lot about engineering	☐	☐	☐	☐	☐
I would be confident talking about engineering in lessons	☐	☐	☐	☐	☐

How much do you agree with the following statements? Please tick the relevant box for each statement below.

	Strongly disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly agree
I am good at finding patterns and seeing how things fit together	☐	☐	☐	☐	☐
I am good at looking for problems and checking things are right	☐	☐	☐	☐	☐
I am good at imagining and picturing what things might look like	☐	☐	☐	☐	☐
I am good at trying different ways to make things better	☐	☐	☐	☐	☐
I am good at fixing problems and finding solutions	☐	☐	☐	☐	☐
I am good at trying things, testing ideas, and changing my plans if necessary	☐	☐	☐	☐	☐

Engineering in your life and community

How much do you agree with the following statements? Please tick the relevant box for each statement below.

	Strongly disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly agree
Being interested in engineering is an important part of who I am	☐	☐	☐	☐	☐
I think of myself as an engineering-type person	☐	☐	☐	☐	☐
It is important people think of me as an engineering-type person	☐	☐	☐	☐	☐
It is important to me that I have other engineering-type people to talk about engineering with	☐	☐	☐	☐	☐
I know how to talk about engineering using technical words and language	☐	☐	☐	☐	☐
I am comfortable having conversations about engineering	☐	☐	☐	☐	☐
There is a history of engineering within my local community	☐	☐	☐	☐	☐
There is a history of engineering within my family tree	☐	☐	☐	☐	☐
There is a history of making and fixing things within my local community	☐	☐	☐	☐	☐
There is a history of making and fixing things within my family tree	☐	☐	☐	☐	☐

Science, engineering and the media

How often do you do the following things outside of school? Tick the appropriate box below.

	Never or rarely (once in a year)	Occasionally (few times a year)	Sometimes (once every month)	Regularly (once every week)	Always (every day or every other day)
Read books or magazines about science?	☐	☐	☐	☐	☐
Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.?	☐	☐	☐	☐	☐
Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.?	☐	☐	☐	☐	☐
Read books or magazines about engineering?	☐	☐	☐	☐	☐
Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	☐	☐	☐	☐	☐

More about you

How often do you do the following things when you are not in school? Please tick the relevant box for each statement below.

	Never	At least once, but more than a year ago	At least once a year	At least once a term	At least once a month
Go to a museum?	☐	☐	☐	☐	☐
Go to a science centre, science museum, or planetarium?	☐	☐	☐	☐	☐
Visit a zoo or aquarium?	☐	☐	☐	☐	☐
Do DIY, or help fix things around the home?	☐	☐	☐	☐	☐
Get shown how to use tools?	☐	☐	☐	☐	☐
Make models, e.g. playing with Lego, painting miniatures?	☐	☐	☐	☐	☐
Do crafts, e.g. knitting, woodwork?	☐	☐	☐	☐	☐
Play videogames about designing or building, e.g. The Sims, Minecraft?	☐	☐	☐	☐	☐
Program computers, e.g. writing apps, building websites?	☐	☐	☐	☐	☐

How often do you do the following things when you are in school? Please tick the relevant box for each statement below.

	Never	At least once, but more than a year ago	At least once a year	At least once a term	At least once a month
Go to an after school science club?	☐	☐	☐	☐	☐
Go to an after school club that involves engineering?	☐	☐	☐	☐	☐
Had people visit you in school to teach you about engineering?	☐	☐	☐	☐	☐
Take an engineering related school trip?	☐	☐	☐	☐	☐
Take a school trip to a museum?	☐	☐	☐	☐	☐
Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes?	☐	☐	☐	☐	☐
Take part in a competition where you design or make something?	☐	☐	☐	☐	☐
Go to a club where you make things?	☐	☐	☐	☐	☐

Going to the museum

How much do you agree with the following statements? Please tick the relevant box for each statement below.

	Strongly disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly agree
My family like going to museums	☐	☐	☐	☐	☐
I like going to museums	☐	☐	☐	☐	☐
I have learnt a lot about engineering from museums	☐	☐	☐	☐	☐

Participation in science

Have you participated in any science education programmes or competitions? e.g. CREST Award, Project Bloodhound, Science Fairs, Olympiads, or other challenges.

☐ Yes ☐ No

If you have participated and answered yes, please name the competitions or programmes in the box below.

If you have not participated and answered no, which of the statements below best describes why not?

- ☐ I intend to do them next year
- ☐ I am interested but my school is not involved in any
- ☐ I heard about them but I am not interested
- ☐ I don't know anything about them but I might be interested
- ☐ I don't know anything about them and I am not interested

Participation in engineering

Have you participated in any engineering education programmes or competitions? E.g. Secondary Engineer, Science Fairs, Ultimate STEM Challenge, or other challenges.

☐ Yes ☐ No

If you have participated and answered yes, please name the competitions or programmes in the box below.

If you have not participated and answered no, which of the statements below best describes why not?

- ☐ I intend to do them next year
- ☐ I am interested but my school is not involved in any
- ☐ I heard about them but I am not interested
- ☐ I don't know anything about them but I might be interested
- ☐ I don't know anything about them and I am not interested

Science and engineering in schools

How much do you agree with the following statements? Please tick the relevant box for each statement below.

	Strongly disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly agree
My teachers have specifically encouraged me to continue with science after GCSEs	☐	☐	☐	☐	☐
My teachers have explained to me that science is useful for my future	☐	☐	☐	☐	☐
I don't think I am clever enough to study any science at A-Level after my GCSEs	☐	☐	☐	☐	☐
My teachers explain how engineering qualifications can lead to different jobs	☐	☐	☐	☐	☐
My teachers have specifically encouraged me to consider studying engineering after GCSEs	☐	☐	☐	☐	☐
My teachers have explained to me that understanding engineering is useful for my future	☐	☐	☐	☐	☐
I don't think I am clever enough to study any engineering after GCSE	☐	☐	☐	☐	☐

Science and engineering in everyday life

How much do you agree with the following statements? Please tick the relevant box for each statement below.

	Strongly disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly agree
It is useful to know about science in my daily life	☐	☐	☐	☐	☐
Engineers need to be imaginative in their work	☐	☐	☐	☐	☐
Engineering creates new jobs so more people can have work	☐	☐	☐	☐	☐
It is useful to know about engineering in my daily life	☐	☐	☐	☐	☐
Getting young people to understand engineering is important for our society	☐	☐	☐	☐	☐

Understanding the school setting

How much do you agree with the following statements? Please tick the relevant box for each statement below.

	Strongly disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly agree
I know what the rules of my classrooms are	☐	☐	☐	☐	☐
I always follow the rules of my classrooms	☐	☐	☐	☐	☐
I know the safety rules for using tools and materials in my classrooms	☐	☐	☐	☐	☐
I always follow the safety rules for using tools and materials in my classrooms	☐	☐	☐	☐	☐
I know about what engineering qualifications I could study after my GCSEs	☐	☐	☐	☐	☐

Questions continue on the next page…

Working in a science job

Do you think you might like to work in a science-related job in the future?

☐ Yes

☐ No

If you said yes you think you might like to work in a science-related job in the future can you tell us why? You can select multiple answers below.

☐ Opportunity to help others
☐ Well paid
☐ Secure
☐ Well respected/high status
☐ Good work-life balance
☐ Personally satisfying
☐ Lots of different types of job available
☐ Interesting
☐ Opportunities to make exciting new discoveries
☐ Opportunities to fix real world problems
☐ Don't know
☐ Other (please specify): _________________

If you said no you do not think you would like to have a science-related job in the future can you tell us why not? You can select multiple answers below.

☐ Long hours
☐ Poorly paid
☐ Too competitive
☐ Hard to get into
☐ No real chance of making a difference
☐ Uncool
☐ Boring
☐ Need too many qualifications
☐ Difficult area for people of my background to get into
☐ Just want to do something else
☐ Bad image
☐ Limited range of job opportunities available
☐ Don't understand what the jobs would involve
☐ Messy work
☐ The work would be too difficult
☐ Don't know
☐ Other (please specify): ___________________

Working in an engineering job

Do you think you might like to work in an engineering-related job in the future?

☐ Yes

☐ No

If you said yes you think you might like to work in an engineering-related job in the future can you tell us why? You can select multiple answers below.

☐ Opportunity to help others
☐ Well paid
☐ Secure
☐ Well respected/high status
☐ Good work-life balance
☐ Personally satisfying
☐ Lots of different types of job available
☐ Interesting
☐ Opportunities to make things
☐ Opportunity to fix real world problems
☐ Don't know
☐ Other (please specify): _____________

If you said no you do not think you would like to have an engineering-related job in the future can you tell us why not? You can select multiple answers below.

☐ Long hours
☐ Poorly paid
☐ Too competitive
☐ Hard to get into
☐ No real chance of making a difference
☐ Uncool
☐ Boring
☐ Need too many qualifications
☐ Difficult area for people of my background to get into
☐ Just want to do something else
☐ Bad image
☐ Limited range of job opportunities available
☐ Don't understand what the jobs would involve
☐ Messy work
☐ The work would be too difficult
☐ Don't know
☐ Other (please specify): ____________________

How likely is it that you would tell the following people about your interest or lack of interest in engineering?

	I would not talk to them about it	I would think about mentioning it	I might mention it	I would probably mention it	I would definitely mention it
A family member	☐	☐	☐	☐	☐
A teacher	☐	☐	☐	☐	☐
A friend	☐	☐	☐	☐	☐
A new classmate	☐	☐	☐	☐	☐

Future for science and engineering

Although it is a long way off which of the following describes your views:

☐ I would like to study science at university
☐ I would like to study one or more sciences at A-level (E.g. biology, chemistry, physics)
☐ I would like to study some science after GCSE but not A-level biology, chemistry, physics
☐ I do not want to study any science after GCSE
☐ None of the above or I don't know

Although it is a long way off which of the following describes your views:

☐ I would like to study engineering at university
☐ I would like to study engineering at college/sixth form
☐ I would like to study engineering after GCSE but not A-level
☐ I do not want to study any engineering after GCSE
☐ None of the above or I don't know

Science and engineering engagement

How much do you agree with the following statements? Please tick the relevant box for each statement below.

	Strongly disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly agree
I believe I could be successful at science in the future	☐	☐	☐	☐	☐
I think understanding science is important	☐	☐	☐	☐	☐
I enjoy learning about science	☐	☐	☐	☐	☐
I think learning about science is interesting	☐	☐	☐	☐	☐
I think it is useful to know about science	☐	☐	☐	☐	☐
Learning about science takes too much effort	☐	☐	☐	☐	☐
I think learning about science is boring	☐	☐	☐	☐	☐
I worry I am not good at science	☐	☐	☐	☐	☐
I want to learn more about science	☐	☐	☐	☐	☐
I want to learn more about science, even if it is hard	☐	☐	☐	☐	☐
It would be good for my future to learn about science	☐	☐	☐	☐	☐

How much do you agree with the following statements? Please tick the relevant box for each statement below.

	Strongly disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly agree
I believe I could be successful at engineering in the future	☐	☐	☐	☐	☐
I think understanding engineering is important	☐	☐	☐	☐	☐
I enjoy learning about engineering	☐	☐	☐	☐	☐
I think learning about engineering is interesting	☐	☐	☐	☐	☐
I think it is useful to know about engineering	☐	☐	☐	☐	☐
Learning about engineering takes too much effort	☐	☐	☐	☐	☐
I think learning about engineering is boring	☐	☐	☐	☐	☐
I worry I am not good at engineering	☐	☐	☐	☐	☐
I want to learn more about engineering	☐	☐	☐	☐	☐
I want to learn more about engineering, even if it is hard	☐	☐	☐	☐	☐
It would be good for my future to learn about engineering	☐	☐	☐	☐	☐

Thank you for answering these questions. Would you like to submit your answers to our study?

If you submit these we will not be able to remove them later if you change your mind as your name will not be attached to your answers.

Tick yes to submit your answers for our study and finish the task.

Tick no and your answers will not be used in the study.

Would you like to submit your answers to this study?

☐ Yes ☐ No

Thank you for taking part in this study

Thank you for taking part in this study. Taking part will help us to better understand how young people in the UK see and experience science and engineering and help us understand how to teach these subjects.

If you chose to submit your answers they will be combined with all the answers we collect from students like you in the UK and then looked at to find patterns. We will talk about what we have learned in reports and share our findings with others but you will not be identified. Because your name is not attached to your data we cannot remove it now that it has been submitted.

If you have any questions please contact:

Rory McDonald, University of Central Lancashire, RAMcDonald5@uclan.ac.uk

Dr Richard Davies, University of Central Lancashire, RDavies15@uclan.ac.uk

General Cultural Capital Instrument

Item	**Response Scale**
Did your mother leave school before age 16?	-1 to 1 three-point Likert scale
Did your mother go to university?	-1 to 1 three-point Likert scale
Did your father leave school before age 16?	-1 to 1 three-point Likert scale
Did your father go to university?	-1 to 1 three-point Likert scale
Approximately how many books, including e-books, are there in your home?	0 to 2 five-point Likert scale
How often do you do the following things when you are not in school: go to a museum?	0 to 2 five-point Likert scale

Science Capital Instrument

Item	**Response Scale**
A science qualification can help you get many different types of job	-2 to 2 five-point Likert scale
When you are not in school, how often do you talk about science with other people?	0 to 4 five-point Likert scale
One or both of my parents think science is very interesting	-1 to 1 five-point Likert scale
One or both of my parents has explained to me that science is useful for my future	-1 to 1 five-point Likert scale
I know how to use scientific evidence to make an argument	-2 to 2 five-point Likert scale
How often do you go to an after-school science club?	0 to 4 five-point Likert scale
When not in school, how often do you read books/magazines about science?	0 to 4 five-point Likert scale
When not in school, how often do you go to a science centre, science museum, or planetarium?	0 to 4 five-point Likert scale
When not in school, how often do you visit a zoo or aquarium?	0 to 4 five-point Likert scale
My teachers have specifically encouraged me to continue with science after GCSE/National 5s	-2 to 2 five-point Likert scale
My teachers have explained to me that science is useful for my future	-2 to 2 five-point Likert scale
It is useful to know about science in my daily life	-1 to 1 five-point Likert scale
Who do you talk with about science?	0 to 3.5 scale based on number of contacts
Do you know anyone (family, friends, or community) that works as a scientist or in a job that uses science?	0 to 7 scale based on number of contacts

Archer-Style Engineering Capital Instrument

Item	Response Scale
An engineering qualification can help you to get many different types of job	-2 to 2 five-point Likert scale
When you are not in school, how often do you talk about engineering with other people?	0 to 4 five-point Likert scale
One or both of my parents think engineering is very interesting	-1 to 1 five-point Likert scale
One or both of my parents has explained to me that engineering is useful for my future	-1 to 1 five-point Likert scale
I know how to design and make things	-2 to 2 five-point Likert scale
How often do you go to an after-school club that involves engineering?	0 to 4 five-point Likert scale
When not in school, how often do you read books/magazines about engineering?	0 to 4 five-point Likert scale
When not in school, how often do you go to a science centre, science museum, or planetarium?	0 to 4 five-point Likert scale
My teachers have specifically encouraged me to consider studying engineering after GCSE/National 5s	-2 to 2 five-point Likert scale
My teachers have explained to me that understanding engineering is useful for my future	-2 to 2 five-point Likert scale
It is useful to know about engineering in my daily life	-1 to 1 five-point Likert scale
Who do you talk with about engineering?	0 to 4 scale based on number of contacts
Do you know anyone (family, friends, or community) that works as an engineer or in a job that uses engineering?	0 to 7 scale based on number of contacts

Engineering Capital Instrument

Item	Response Scale
I have learnt a lot about engineering from museums	-2 to 2 five-point Likert scale
I know how to design and make things	-2 to 2 five-point Likert scale
I know quite a lot about engineering	-2 to 2 five-point Likert scale
I would be confident talking about engineering in lessons	-2 to 2 five-point Likert scale
An engineering qualification can help you get many different types of job	-2 to 2 five-point Likert scale
When you are not in school, how often do you talk about engineering with other people?	0 to 4 five-point Likert scale
How often do you do the following things outside of school: Read books or magazines about engineering?	0 to 4 five-point Likert scale
How often do you do the following things outside of school: Go online to gind out about engineering, e.g. YouTube, engineering websites, play engineering games?	0 to 4 five-point Likert scale
How often do you do the following things when you are not in school: Do DIY, or help fix things around the home?	0 to 4 five-point Likert scale
How often do you do the following things when you are not in school: Do crafts, e.g. knitting, woodworking?	0 to 4 five-point Likert scale (Reverse code)
How often do you do the following things when you are in school: Take an engineering-related school trip?	0 to 4 five-point Likert scale (Reverse code)

Engineering Identity Instrument

Item	Response Scale
People who are like me work in engineering	-2 to 2 five-point Likert scale
Other people think of me as an engineering-type person	-2 to 2 five-point Likert scale
My teachers have specifically encouraged me to consider studying engineering after GCSE/National 5s	-2 to 2 five-point Likert scale
I don’t think I am clever enough to study engineering after GCSE/National 5s	-2 to 2 five-point Likert scale

Engineering Engagement Instrument

Item	Response Scale
I believe I could be successful at engineering in the future.	-2 to 2 five-point Likert scale
I know quite a lot about engineering.	-2 to 2 five-point Likert scale
I think understanding engineering is important.	-2 to 2 five-point Likert scale
I enjoy learning about engineering.	-2 to 2 five-point Likert scale
I think learning about engineering is interesting.	-2 to 2 five-point Likert scale
I think it is useful to know about engineering.	-2 to 2 five-point Likert scale
Learning about engineering takes too much effort (reverse coded).	-2 to 2 five-point Likert scale
I think learning about engineering is boring (reverse coded).	-2 to 2 five-point Likert scale
I worry I am not good at engineering (reverse coded).	-2 to 2 five-point Likert scale
I want to learn more about engineering.	-2 to 2 five-point Likert scale
I want to learn more about engineering even if it is hard.	-2 to 2 five-point Likert scale
It would be good for my future to learn about engineering.	-2 to 2 five-point Likert scale

Directory of Statistical Analyses Outputs for Chapter Four

Cronbach’s Alpha: Science Capital Instrument

A Cronbach’s Alpha analysis was utilised to examine the internal consistency (reliability) of responses on the science capital instrument scale. Fourteen items were examined and determined to possess a high level of internal consistency (N=854, a=0.851 based on standardised items) supporting the use of this scale. This result was not meaningfully improved by the removal of any of the items.

Case Processing Summary

		N	%
Cases	Valid	854	92.7
	Excluded[a]	67	7.3
	Total	921	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.833	.851	14

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
28.1. A science qualification can help you to get many different types of job	8.888	45.678	.374	.222	.828
29. When you are not in school how often do you talk about science with other people?	8.235	38.064	.620	.493	.812
39.3. ...Think science is very interesting"	9.691	45.904	.612	.496	.820
39.4. ...Has explained to me that science is useful for my future"	9.706	45.888	.567	.456	.821
40.2. I know how to use scientific evidence to make an argument	9.701	41.844	.540	.326	.817
45.1. Go to an after school science club?	9.535	44.975	.371	.167	.829

43.1. Read books or magazines about science?	9.005	41.697	.528	.322	.818
44.2. Go to a science centre, science museum, or planetarium?	8.821	43.291	.541	.418	.818
44.3. Visit a zoo or aquarium?	8.317	46.627	.266	.243	.835
51.1. My teachers have specifically encouraged me to continue with science after GCSEs	10.042	42.665	.501	.350	.820
51.2. My teachers have explained to me that science is useful for my future	9.346	43.659	.442	.351	.824
Science Capital Talk With Science Score	8.960	44.494	.591	.410	.817
TOTAL KNOWING SOMEONE	9.222	44.932	.346	.145	.831
52.1. It is useful to know about science in my daily life	9.641	46.279	.575	.389	.822

Cronbach's Alpha: Archer-Style Engineering Capital Instrument

A Cronbach's Alpha analysis was utilised to examine the internal consistency (reliability) of responses on the Archer-style engineering capital scale instrument. Thirteen items were examined and determined to possess a high level of internal consistency (N=846, a=0.840 based on standardized items) supporting the use of this scale. This result was not meaningfully improved by the removal of any of the items.

Case Processing Summary

		N	%
Cases	Valid	846	91.9
	Excluded[a]	75	8.1
	Total	921	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.818	.840	13

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
28.3. An engineering qualification can help you get many different types of job	4.371	36.325	.380	.216	.812
AS Eng Cap Talk with Engineering	4.439	35.770	.619	.489	.797
31. When you are not in school how often do you talk about engineering with other people?	3.933	30.515	.622	.548	.791
COPY FOR AS ENG CALC 39.7. ...Has explained to me that understanding engineering is useful for my future"	5.031	37.048	.582	.534	.803

COPY FOR AS ENG 39.5. ...Think that engineering is very interesting"	4.881	37.146	.584	.550	.803
40.6. I know how to design and make things	4.683	35.153	.387	.171	.813
45.2. Go to an after school club that involves engineering?	4.797	37.486	.358	.185	.813
43.4. Read books or magazines about engineering?	4.439	34.836	.504	.319	.802
44.2. Go to a science centre, science museum, or planetarium?	3.954	36.840	.322	.166	.816
51.5. My teachers have specifically encouraged me to consider studying engineering after GCSEs	5.696	34.175	.520	.531	.800
51.6. My teachers have explained to me that understanding engineering is useful for my future	5.349	32.940	.564	.569	.796
TOTAL KNOWING SOMEONE ENGINEERING	4.217	36.458	.292	.132	.821
COPY FOR AS ENG CAP SCORE 52.4. It is useful to know about engineering in my daily life	4.920	37.344	.567	.377	.804

Cronbach’s Alpha: General Cultural Capital Instrument

A Cronbach’s Alpha analysis was utilised to examine the internal consistency (reliability) of responses on the general cultural capital scale instrument. Six items were examined and determined to possess a medium level of internal consistency (N=889, a=0.575) supporting the use of this scale. This result was not meaningfully improved by the removal of any of the items.

Case Processing Summary

		N	%
Cases	Valid	889	96.5
	Excluded[a]	32	3.5
	Total	921	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.559	.575	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
14. Did your mother leave school before age 16?	2.633	4.356	.240	.160	.539
15. Did your mother go to university?	3.367	3.219	.337	.175	.503
16. Did your father leave school before age 16?	2.769	3.973	.296	.186	.515
17. Did your father go to university?	3.566	3.261	.357	.191	.487
18. Approximately how many books, including e-books, are there in your home?	1.948	4.018	.350	.151	.497
44.1. Go to a museum? (Weighted for general cultural capital)	2.719	4.398	.275	.106	.530

Paired Samples T-Test: Science Capital and Archer-Style Engineering Capital Scores

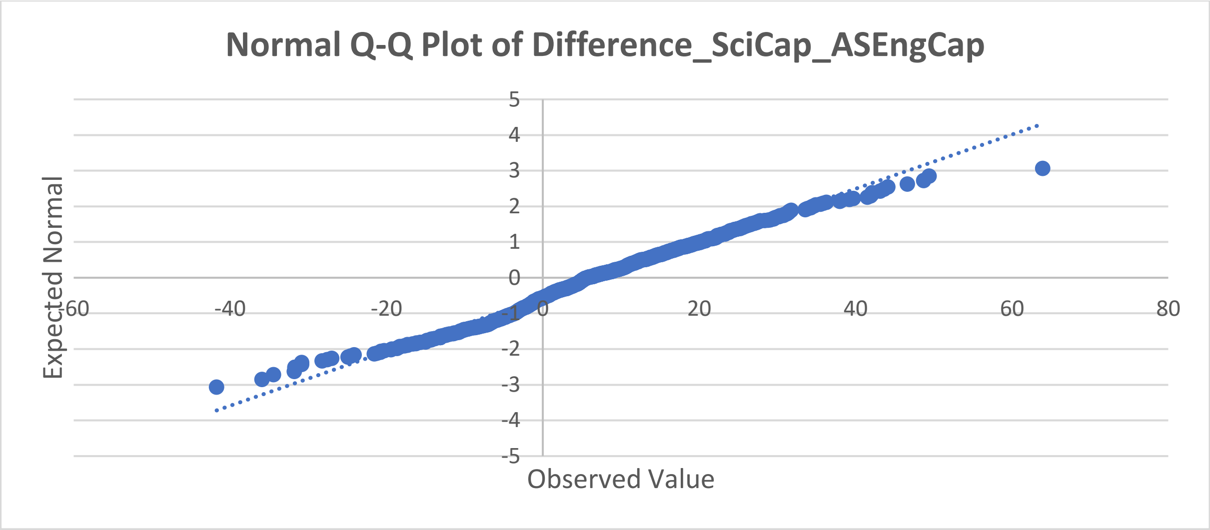
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. A difference score was calculated and examined the determine the influence of outliers and skew/kurtosis within this data. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1. The assumptions underpinning this test were met approving its use.

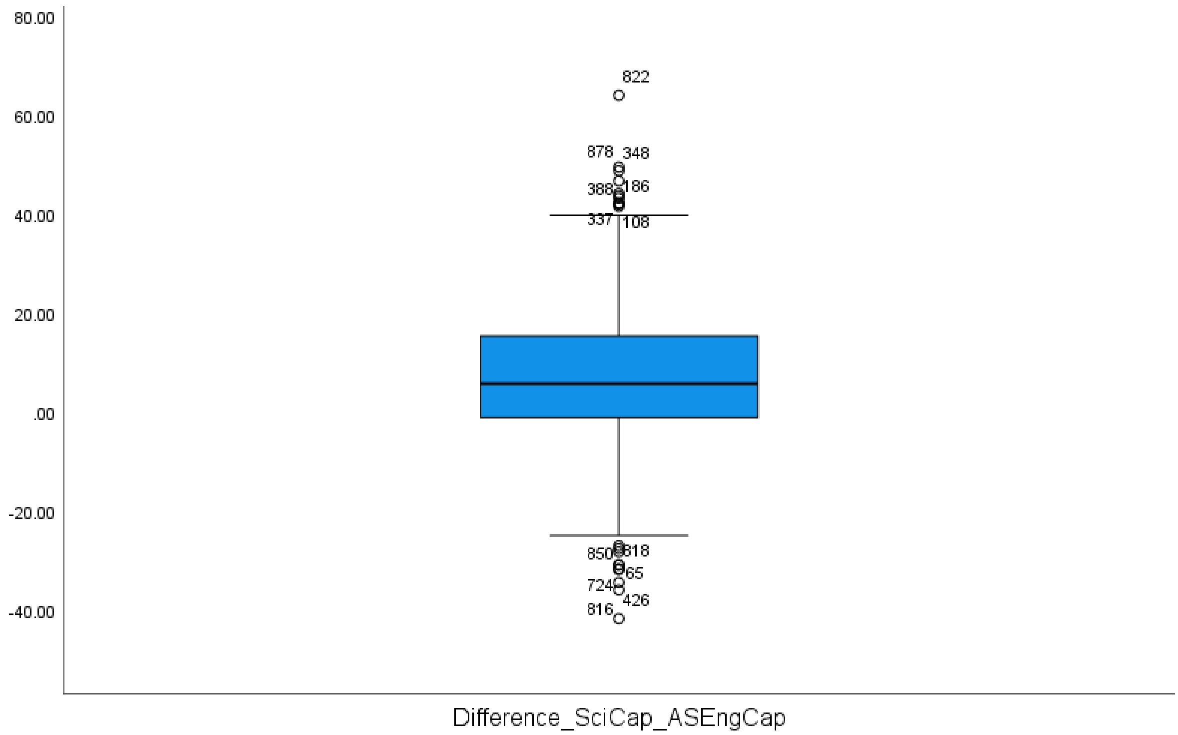
Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Difference_SciCap_ASEngCap	921	100.0%	0	0.0%	921	100.0%

Descriptives

			Statistic	Std. Error
Difference_SciCap_ASEngCap	Mean		7.2109	.42800
	95% Confidence Interval for Mean	Lower Bound	6.3709	
		Upper Bound	8.0509	
	5% Trimmed Mean		7.1645	
	Median		5.7143	
	Variance		168.716	
	Std. Deviation		12.98905	
	Minimum		-41.71	
	Maximum		63.93	
	Range		105.64	
	Interquartile Range		16.57	
	Skewness		.126	.081
	Kurtosis		.990	.161


Normal Q-Q Plot of Difference_SciCap_ASEngCap
Expected Normal
5
4
3
2
1
0
-1
-2
-3
-4
-5
-60
-40
-20
0
20
40
60
80
Observed Value


80.00
60.00
40.00
20.00
.00
-20.00
-40.00
822
878
348
388
186
337
108
850
818
65
724
426
816
Difference_SciCap_ASEngCap

A paired samples t-test revealed that participants possessed significantly greater scores for science capital (M=41.34, SD=14.04) than Archer-style engineering capital (M=34.13, SD=13.50) (t(920)=16.848, p<0.001, d=0.555). The Cohen's d effect size indicates a medium size effect of changing the STEM domain.

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Science Capital Total on 0-105 Scale	41.34	921	14.044	.463
	AS Engineering Capital Total on 0-105 Scale to 0dp	34.13	921	13.501	.445

Paired Samples Correlations

				Significance	
		N	Correlation	One-Sided p	Two-Sided p
Pair 1	Science Capital Total on 0-105 Scale & AS Engineering Capital Total on 0-105 Scale to 0dp	921	.556	<.001	<.001

Paired Samples Test

		Paired Differences							Significance	
					95% Confidence Interval of the Difference					
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	One-Sided p	Two-Sided p
Pair 1	Science Capital Total on 0-105 Scale - AS Engineering Capital Total on 0-105 Scale to 0dp	7.211	12.989	.428	6.371	8.051	16.848	920	<.001	<.001

Paired Samples Effect Sizes

					95% Confidence Interval	
			Standardizer[a]	Point Estimate	Lower	Upper
Pair 1	Science Capital Total on 0-105 Scale - AS Engineering Capital Total on 0-105 Scale to 0dp	Cohen's d	12.989	.555	.486	.624
		Hedges' correction	13.000	.555	.485	.624

a. The denominator used in estimating the effect sizes.
Cohen's d uses the sample standard deviation of the mean difference.
Hedges' correction uses the sample standard deviation of the mean difference, plus a correction factor.

Frequency Analysis: Science Capital and Archer-Style Engineering Capital Groups (Low, Medium, High)

A frequency analysis was utilised to examine the distribution of science and Archer-style engineering capital scores between low (0-34), medium (35-69) and high (70-105) capital groups.

Science Capital Groups

		Frequency	Percent
Valid	Low	311	33.8
	Medium	576	62.5
	High	34	3.7
	Total	921	100.0

AS Engineering Capital Groups

		Frequency	Percent
Valid	Low	525	57.0
	Medium	387	42.0
	High	9	1.0
	Total	921	100.0

Welch's Independent Samples T-Test: Gender Differences and Science Capital Scores

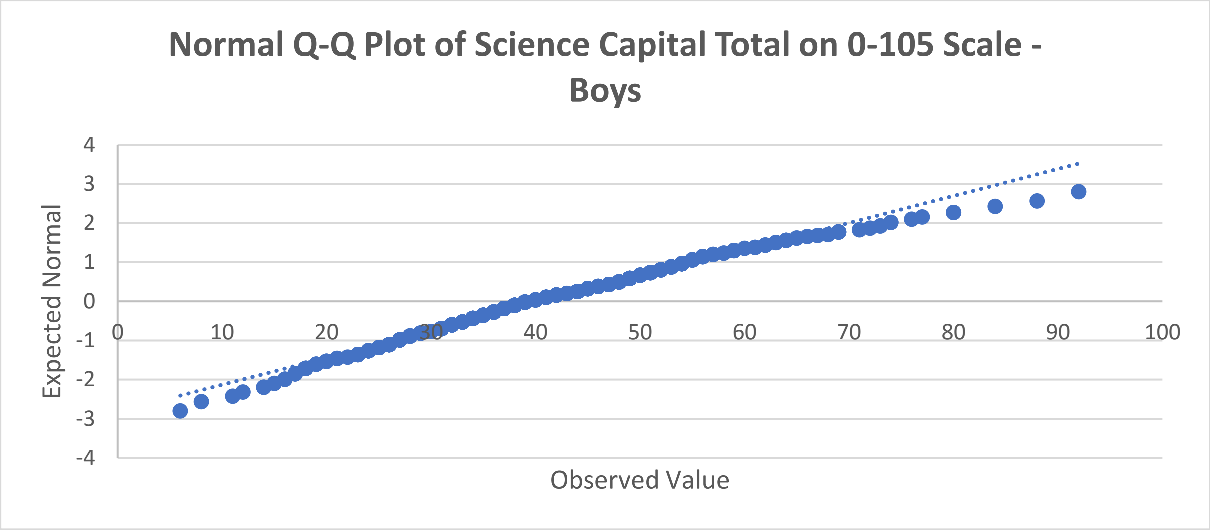
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1. The assumptions underpinning this test were met approving its use.

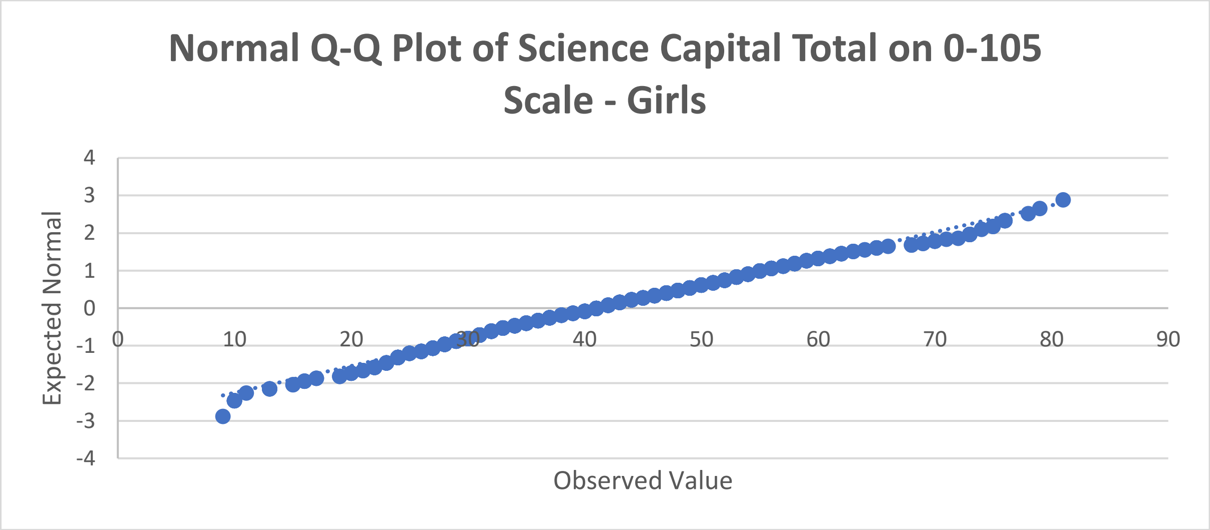
Case Processing Summary

		Cases					
		Valid		Missing		Total	
	2. Are you a girl or a boy?	N	Percent	N	Percent	N	Percent
Science Capital Total on 0-105 Scale	Boy	388	100.0%	0	0.0%	388	100.0%
	Girl	505	100.0%	0	0.0%	505	100.0%

Descriptives

			2. Are you a girl or a boy?			
			Boy		Girl	
			Statistic	Std. Error	Statistic	Std. Error
Science Capital Total on 0-105 Scale	Mean		40.93	.722	41.59	.615
	95% Confidence Interval for Mean	Lower Bound	39.51		40.39	
		Upper Bound	42.35		42.80	
	5% Trimmed Mean		40.49		41.30	
	Median		39.00		41.00	
	Variance		202.450		191.162	
	Std. Deviation		14.229		13.826	
	Minimum		6		9	
	Maximum		92		81	
	Range		86		72	
	Interquartile Range		19		20	
	Skewness		.462	.124	.273	.109
	Kurtosis		.386	.247	-.149	.217


Normal Q-Q Plot of Science Capital Total on 0-105 Scale - Boys


Normal Q-Q Plot of Science Capital Total on 0-105 Scale - Girls

A Welch's independent samples t-test identified no significant difference in the science capital scores of boys (M=40.93, SD=14.229) and girls (M=41.59, SD=13.83) (t(820.579)=-0.697, p=0.486, d=-0.047).

Group Statistics

	2. Are you a girl or a boy?	N	Mean	Std. Deviation	Std. Error Mean
Science Capital Total on 0-105 Scale	Boy	388	40.93	14.229	.722
	Girl	505	41.59	13.826	.615

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Science Capital Total on 0-105 Scale	Equal variances assumed	.124	.725	-.699	891	.242	.485	-.661	.945	-2.516	1.194
	Equal variances not assumed			-.697	820.579	.243	.486	-.661	.949	-2.524	1.201

Welch's Independent Samples T-Test: Gender Differences and Archer-Style Engineering Capital Scores

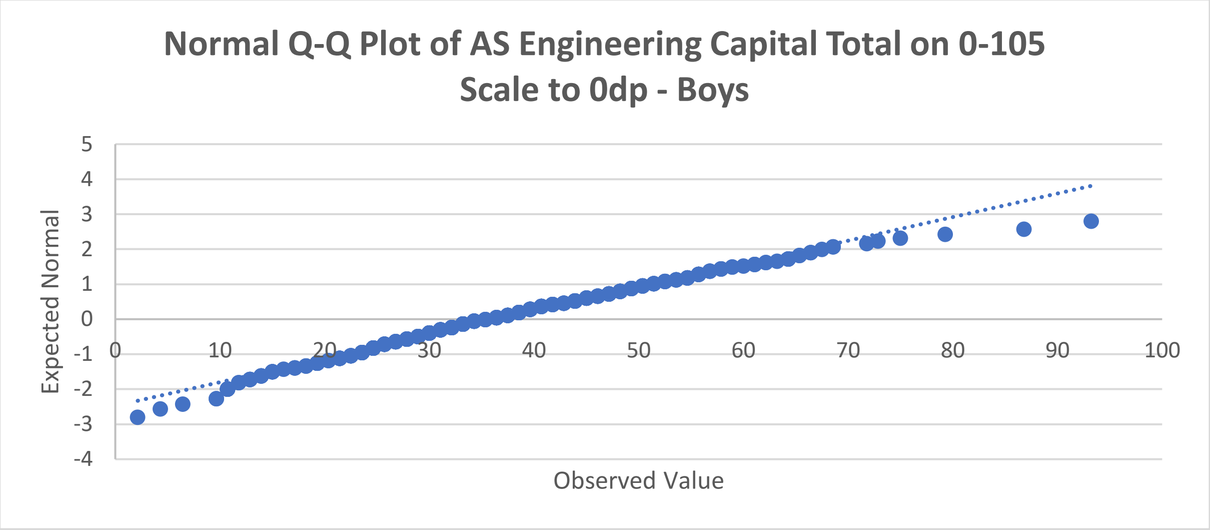
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1. The assumptions underpinning this test were met approving its use.

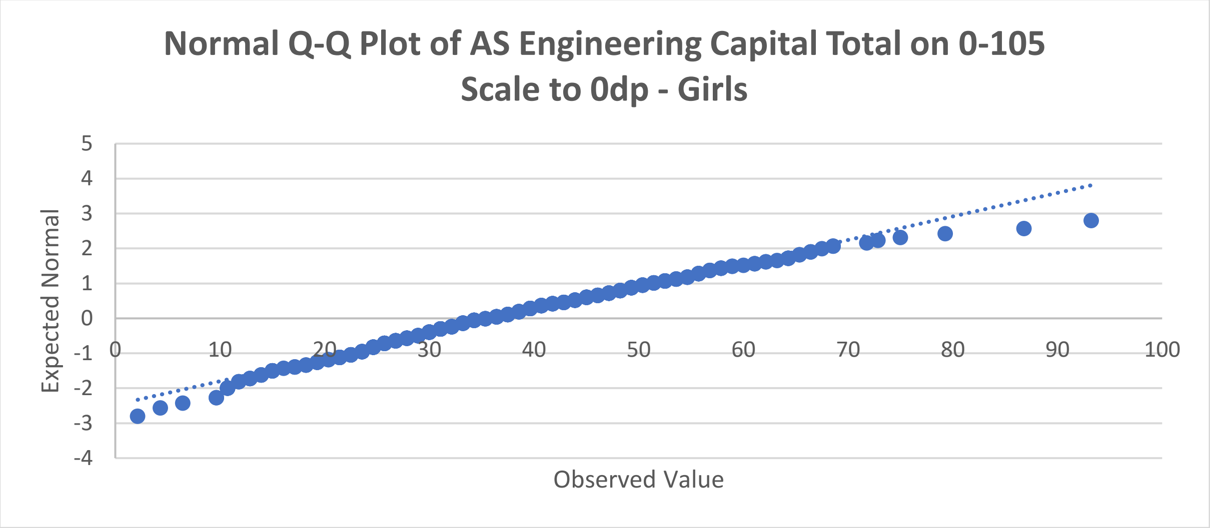
Case Processing Summary

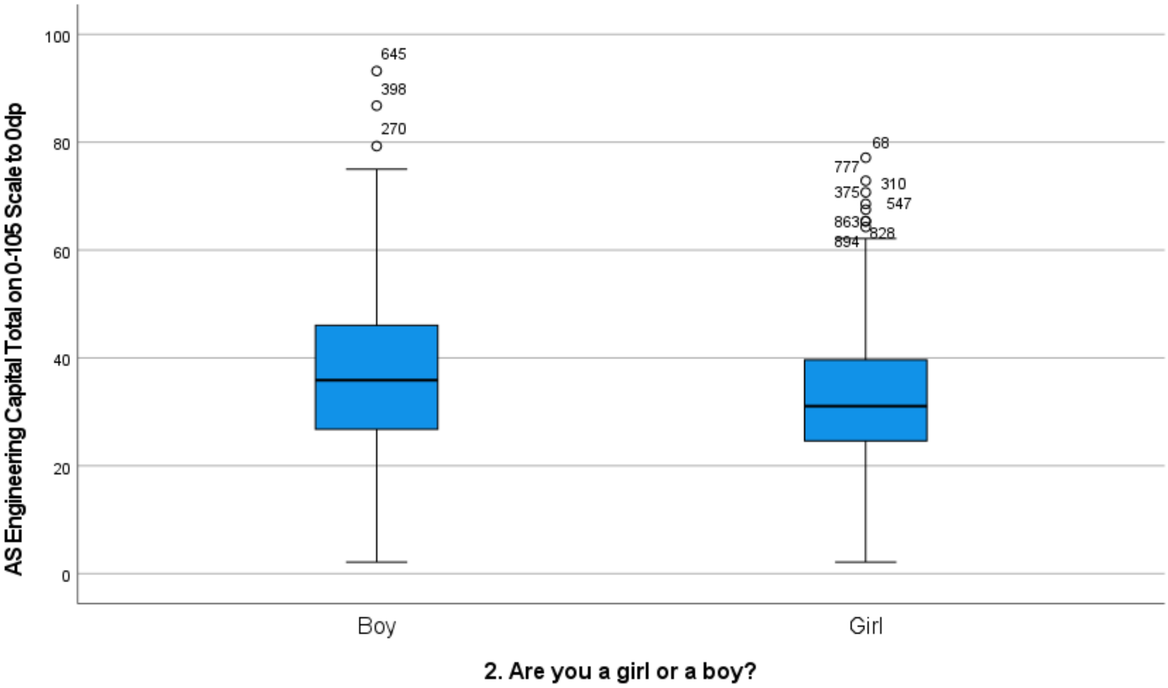
		Cases					
		Valid		Missing		Total	
	2. Are you a girl or a boy?	N	Percent	N	Percent	N	Percent
AS Engineering Capital Total on 0-105 Scale to 0dp	Boy	388	100.0%	0	0.0%	388	100.0%
	Girl	505	100.0%	0	0.0%	505	100.0%

Descriptives

			2. Are you a girl or a boy?			
			Boy		Girl	
			Statistic	Std. Error	Statistic	Std. Error
AS Engineering Capital Total on 0-105 Scale to 0dp	Mean		36.72	.739	32.30	.548
	95% Confidence Interval for Mean	Lower Bound	35.26		31.23	
		Upper Bound	38.17		33.38	
	5% Trimmed Mean		36.33		31.95	
	Median		35.89		31.07	
	Variance		211.794		151.514	
	Std. Deviation		14.553		12.309	
	Minimum		2		2	
	Maximum		93		77	
	Range		91		75	
	Interquartile Range		19		15	
	Skewness		.448	.124	.475	.109
	Kurtosis		.366	.247	.439	.217


Normal Q-Q Plot of AS Engineering Capital Total on 0-105 Scale to 0dp - Boys
Expected Normal
5
4
3
2
1
0
-1
-2
-3
-4
0
10
20
30
40
50
60
70
80
90
100
Observed Value


Normal Q-Q Plot of AS Engineering Capital Total on 0-105 Scale to 0dp - Girls
Expected Normal
5
4
3
2
1
0
-1
-2
-3
-4
0
10
20
30
40
50
60
70
80
90
100
Observed Value


AS Engineering Capital Total on 0-105 Scale to 0dp
100
80
60
40
20
0
645
398
270
68
777
310
375
547
863
828
894
Boy
Girl
2. Are you a girl or a boy?

A Welch's independent samples t-test identified a significant difference in the Archer-style engineering capital scores of boys (M=36.72, SD=14.55) and girls (M=32.30, SD=12.31) (t(754.347)=4.797, p<0.001, d=0.323). The Cohen's d effect size highlights a weak-moderate effect of gender on Archer-style engineering capital scores.

Group Statistics

	2. Are you a girl or a boy?	N	Mean	Std. Deviation	Std. Error Mean
AS Engineering Capital Total on 0-105 Scale to 0dp	Boy	388	36.72	14.553	.739
	Girl	505	32.30	12.309	.548

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
AS Engineering Capital Total on 0-105 Scale to 0dp	Equal variances assumed	13.092	<.001	4.902	891	<.001	<.001	4.412	.900	2.645	6.178
	Equal variances not assumed			4.797	754.347	<.001	<.001	4.412	.920	2.606	6.217

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
AS Engineering Capital Total on 0-105 Scale to 0dp	Cohen's d	13.330	.331	.198	.464
	Hedges' correction	13.342	.331	.197	.464
	Glass's delta	12.309	.358	.224	.492

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

One-Way ANOVA: Science Academic Set Differences and Science Capital Scores

An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1 – the Very Low group did express slightly greater kurtosis however this was deemed within an acceptable margin given the robustness of the ANOVA procedure. The assumptions underpinning this test were met approving its use.

Descriptives

			General Cultural Capital Category									
			Very low		Low		Medium		High		Very high	
			Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error
Science Capital Total on 0-105 Scale	Mean		28.20	2.598	32.80	1.151	38.47	.703	43.05	.749	50.60	1.080
	95% Confidence Interval for Mean	Lower Bound	22.32		30.52		37.09		41.57		48.47	
		Upper Bound	34.08		35.09		39.85		44.52		52.73	
	5% Trimmed Mean		27.72		32.87		38.12		42.65		50.61	
	Median		25.00		32.00		37.00		42.00		50.00	
	Variance		67.511		141.706		169.320		166.160		192.388	
	Std. Deviation		8.217		11.904		13.012		12.890		13.870	
	Minimum		20		6		8		13		16	
	Maximum		45		58		92		88		80	
	Range		25		52		84		75		64	
	Interquartile Range		9		16		20		18		20	
	Skewness		1.469	.687	.068	.234	.464	.132	.459	.142	-.028	.189
	Kurtosis		1.072	1.334	-.497	.463	.669	.263	.404	.282	-.476	.376

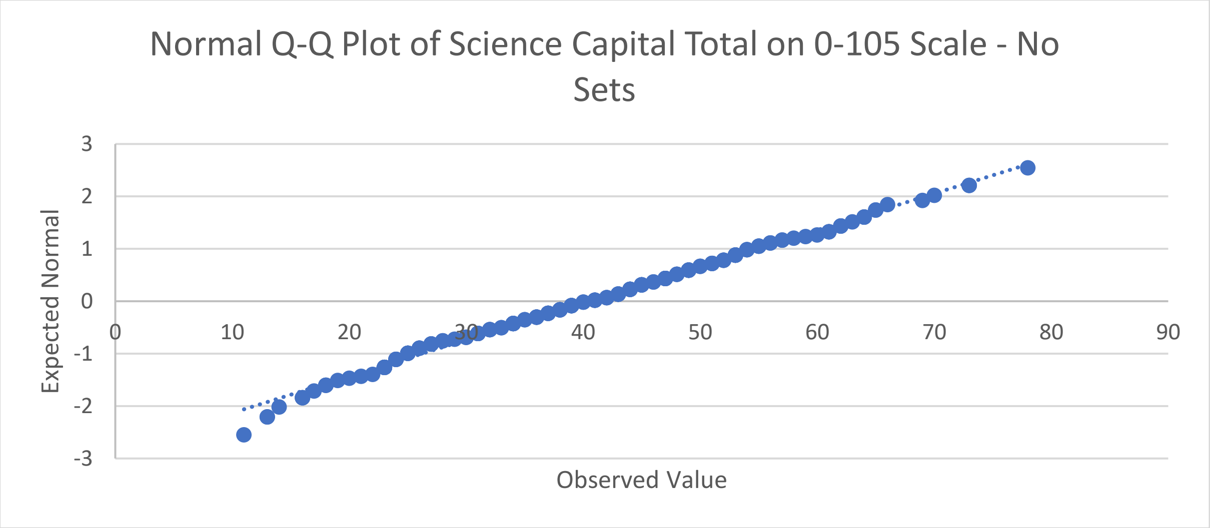
Case Processing Summary

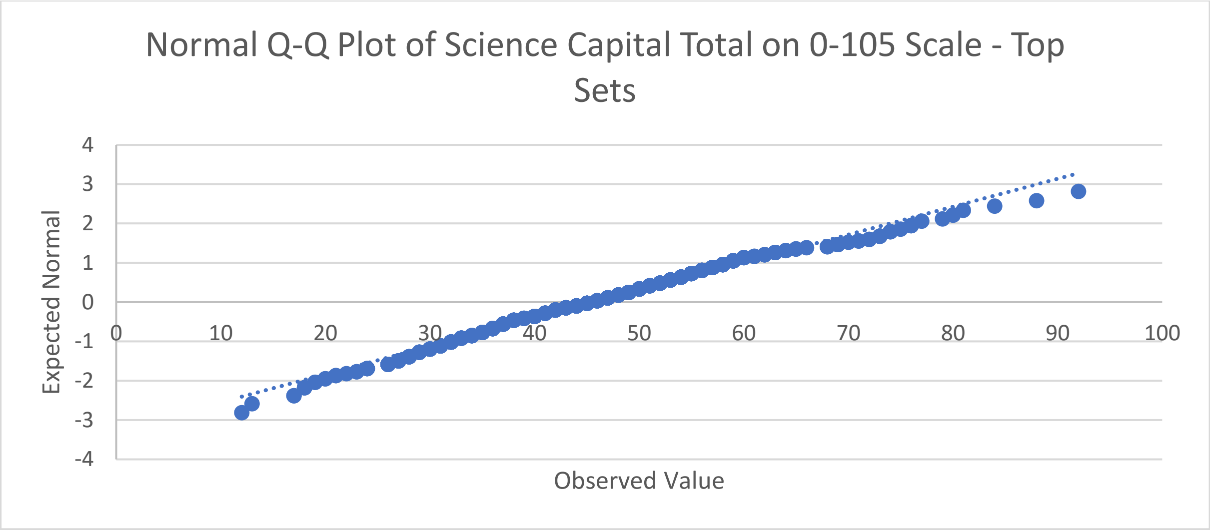
		Cases					
		Valid		Missing		Total	
	25.1.a. Science	N	Percent	N	Percent	N	Percent
Science Capital Total on 0-105 Scale	There are not sets at this school/for this subject	183	100.0%	0	0.0%	183	100.0%
	Top	407	100.0%	0	0.0%	407	100.0%
	Middle	259	100.0%	0	0.0%	259	100.0%
	Bottom	48	100.0%	0	0.0%	48	100.0%

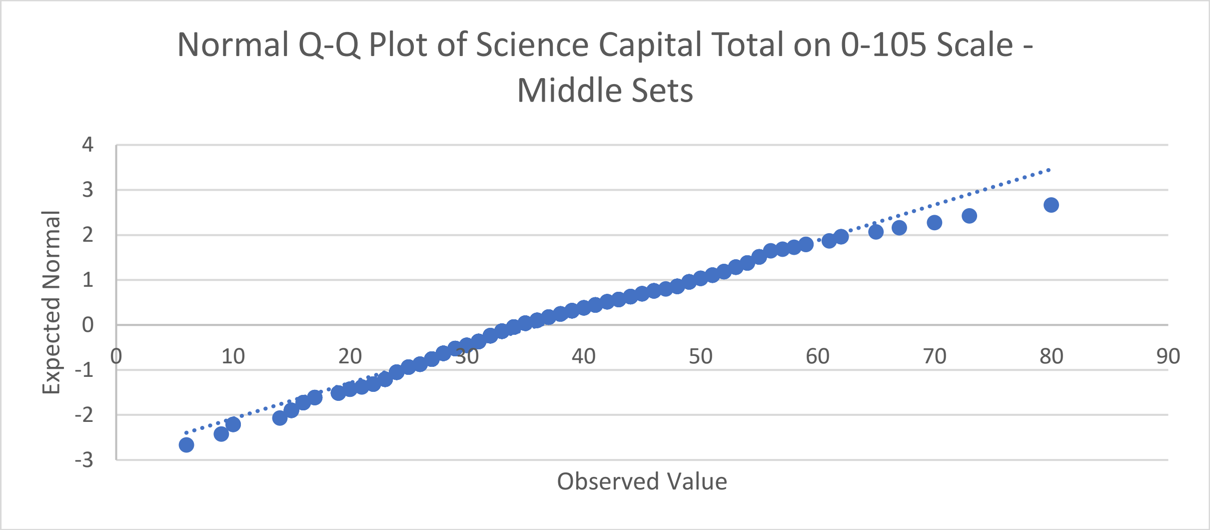
Descriptives

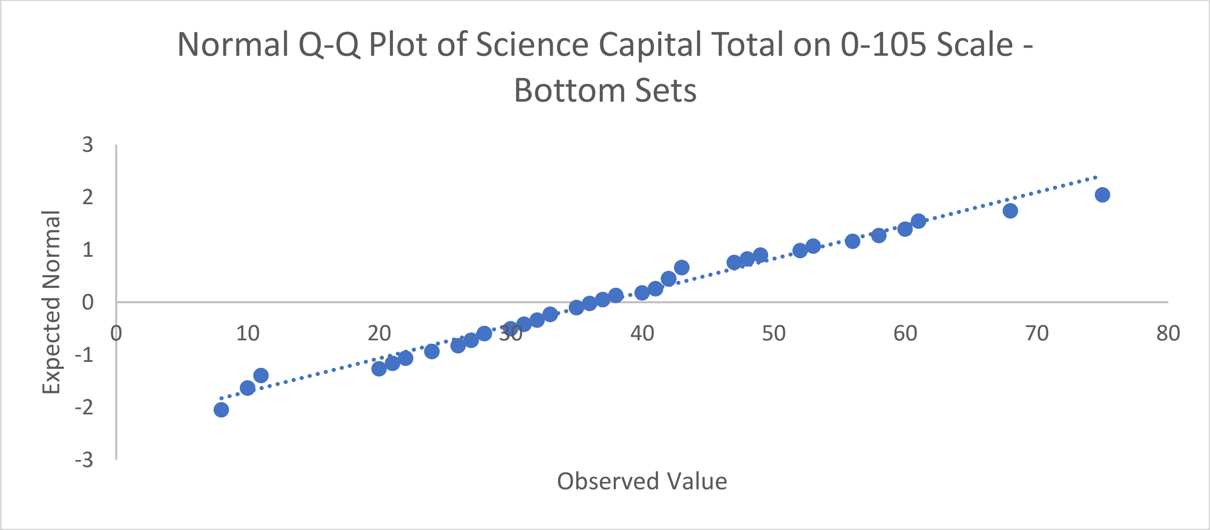
			There are not sets at this school/for this subject		Top		Middle		Bottom	
			Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error
Science Capital Total on 0-105 Scale	Mean		40.56	1.033	45.84	.685	36.27	.766	36.92	2.123
	95% Confidence Interval for Mean	Lower Bound	38.52		44.49		34.76		32.65	
		Upper Bound	42.59		47.19		37.78		41.19	
	5% Trimmed Mean		40.39		45.51		36.01		36.63	
	Median		41.00		45.00		35.00		36.50	
	Variance		195.138		191.203		152.004		216.291	
	Std. Deviation		13.969		13.828		12.329		14.707	
	Minimum		11		12		6		8	
	Maximum		78		92		80		75	
	Range		67		80		74		67	
	Interquartile Range		20		18		17		16	
	Skewness		.148	.180	.374	.121	.415	.151	.266	.343
	Kurtosis		-.472	.357	.140	.241	.233	.302	.242	.674

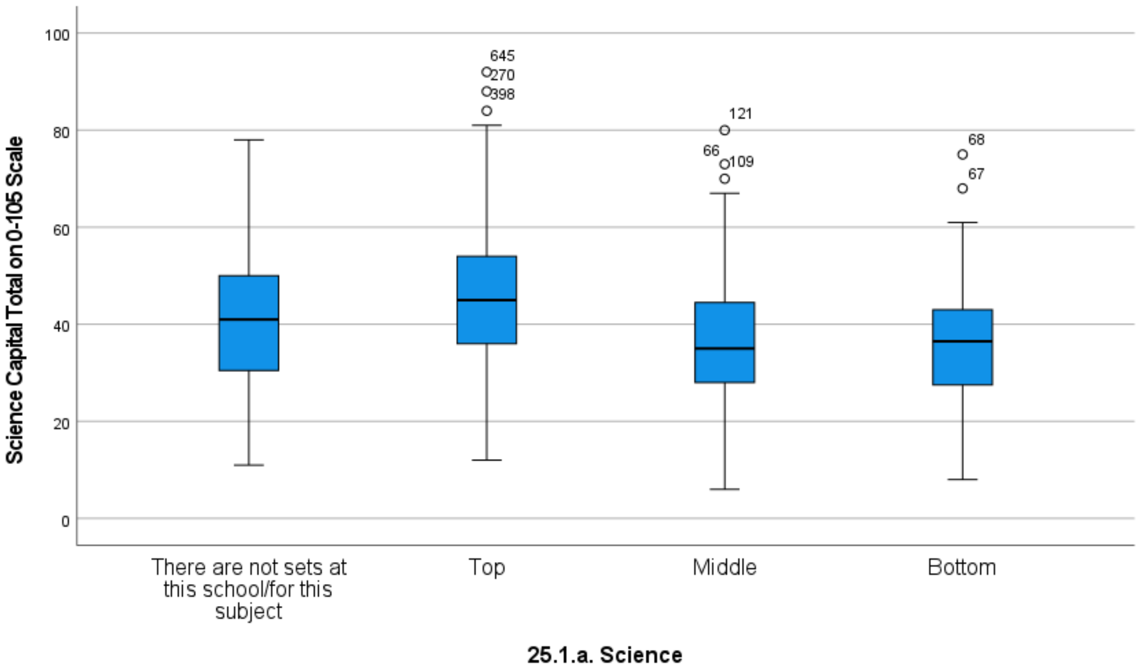
(Column group header: 25.1.a. Science)




Normal Q-Q Plot of Science Capital Total on 0-105 Scale - Top Sets
Expected Normal
4
3
2
1
0
-1
-2
-3
-4
0
10
20
30
40
50
60
70
80
90
100
Observed Value


Normal Q-Q Plot of Science Capital Total on 0-105 Scale - Middle Sets
Expected Normal
4
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
90
Observed Value


Normal Q-Q Plot of Science Capital Total on 0-105 Scale - Bottom Sets
Expected Normal
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
Observed Value


Science Capital Total on 0-105 Scale
100
80
60
40
20
0
645
270
398
121
66
109
68
67
There are not sets at this school/for this subject
Top
Middle
Bottom
25.1.a. Science

A one-way ANOVA was adopted to determine whether science capital scores differed between groups based on school science academic sets. A total of 897 participants were classified into four groups: Top Sets (N=407), Middle Sets (N=259), Bottom Sets (N=48) and No Sets for This Subject (N=183). Science capital scores were found to statistically differ (F(3,893) = 29.160, p<0.001, ETA^2=0.089). Tukey post-hoc testing revealed significant differences in between all groups except No Sets & Bottom Sets and Middle Sets and Bottom Sets. The ETA^2 size of 0.089 indicates a medium-large effect of academic set in shaping science capital scores.

Descriptives

Science Capital Total on 0-105 Scale

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	Upper Bound	Minimum	Maximum
There are not sets at this school/for this subject	183	40.56	13.969	1.033	38.52	42.59	11	78
Top	407	45.84	13.828	.685	44.49	47.19	12	92
Middle	259	36.27	12.329	.766	34.76	37.78	6	80
Bottom	48	36.92	14.707	2.123	32.65	41.19	8	75
Total	897	41.52	14.112	.471	40.60	42.45	6	92

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Science Capital Total on 0-105 Scale	Based on Mean	1.664	3	893	.173
	Based on Median	1.853	3	893	.136
	Based on Median and with adjusted df	1.853	3	882.620	.136
	Based on trimmed mean	1.723	3	893	.161

ANOVA

Science Capital Total on 0-105 Scale

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	15921.312	3	5307.104	29.160	<.001
Within Groups	162526.514	893	182.001		
Total	178447.826	896			

ANOVA Effect Sizes[a]

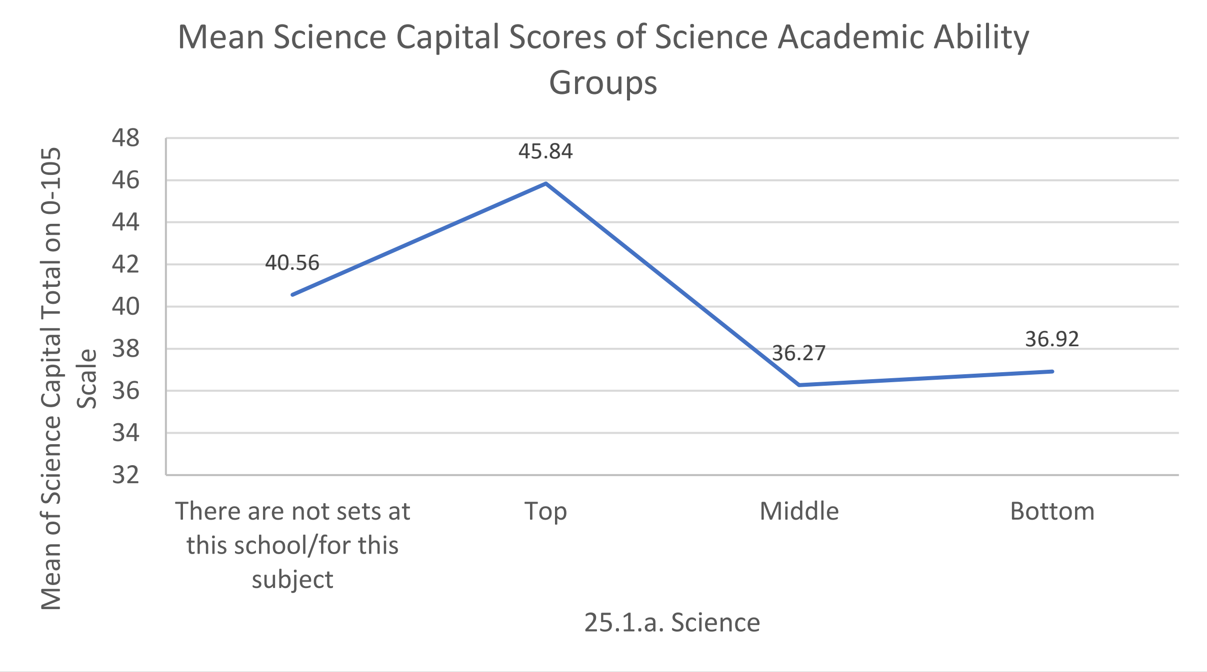
		Point Estimate	95% Confidence Interval Lower	Upper
Science Capital Total on 0-105 Scale	Eta-squared	.089	.055	.124
	Epsilon-squared	.086	.052	.121
	Omega-squared Fixed-effect	.086	.052	.121
	Omega-squared Random-effect	.030	.018	.044

Multiple Comparisons

Dependent Variable: Science Capital Total on 0-105 Scale

	(I) 25.1.a. Science	(J) 25.1.a. Science	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Tukey HSD	There are not sets at this school/for this subject	Top	-5.283*	1.201	<.001	-8.37	-2.19
		Middle	4.287*	1.303	.006	.93	7.64
		Bottom	3.641	2.188	.343	-1.99	9.27
	Top	There are not sets at this school/for this subject	5.283*	1.201	<.001	2.19	8.37
		Middle	9.570*	1.072	.000	6.81	12.33
		Bottom	8.924*	2.059	<.001	3.62	14.22
	Middle	There are not sets at this school/for this subject	-4.287*	1.303	.006	-7.64	-.93
		Top	-9.570*	1.072	.000	-12.33	-6.81
		Bottom	-.646	2.120	.990	-6.10	4.81
	Bottom	There are not sets at this school/for this subject	-3.641	2.188	.343	-9.27	1.99
		Top	-8.924*	2.059	<.001	-14.22	-3.62
		Middle	.646	2.120	.990	-4.81	6.10

*. The mean difference is significant at the 0.05 level.



One-Way ANOVA: Science Academic Set Differences and Archer-Style Engineering Capital Scores

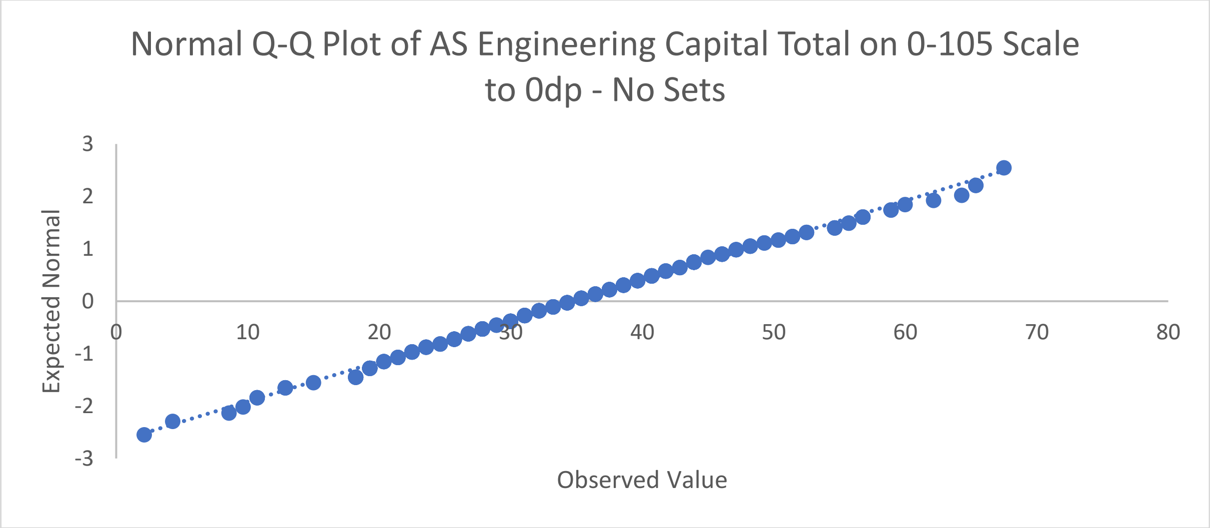
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be largely normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1 – the Bottom Sets group did express slightly greater kurtosis however this was deemed within an acceptable margin given the robustness of the ANOVA procedure. The assumptions underpinning this test were met approving its use.

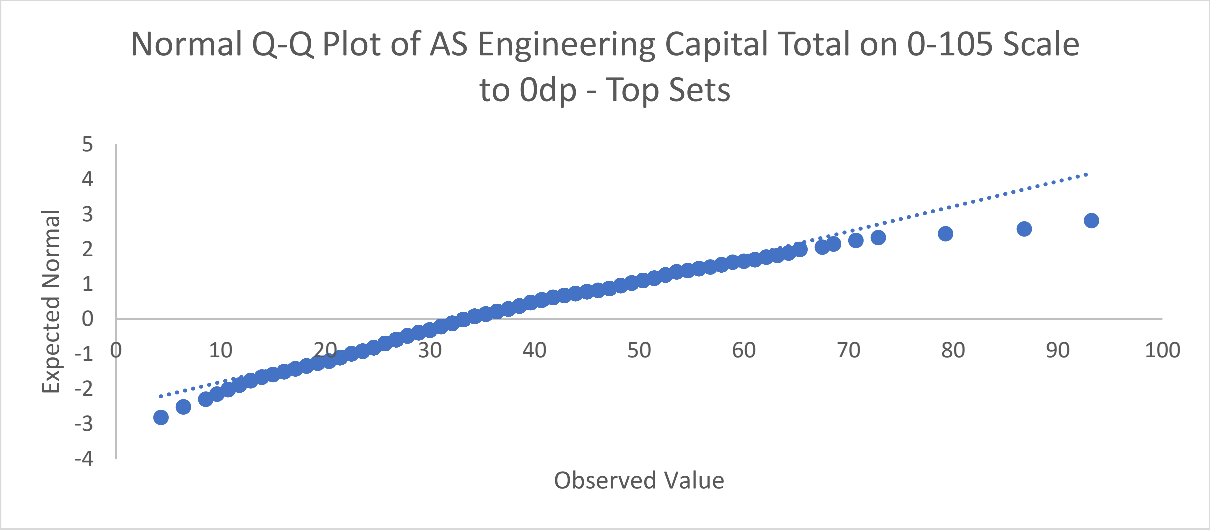
Case Processing Summary

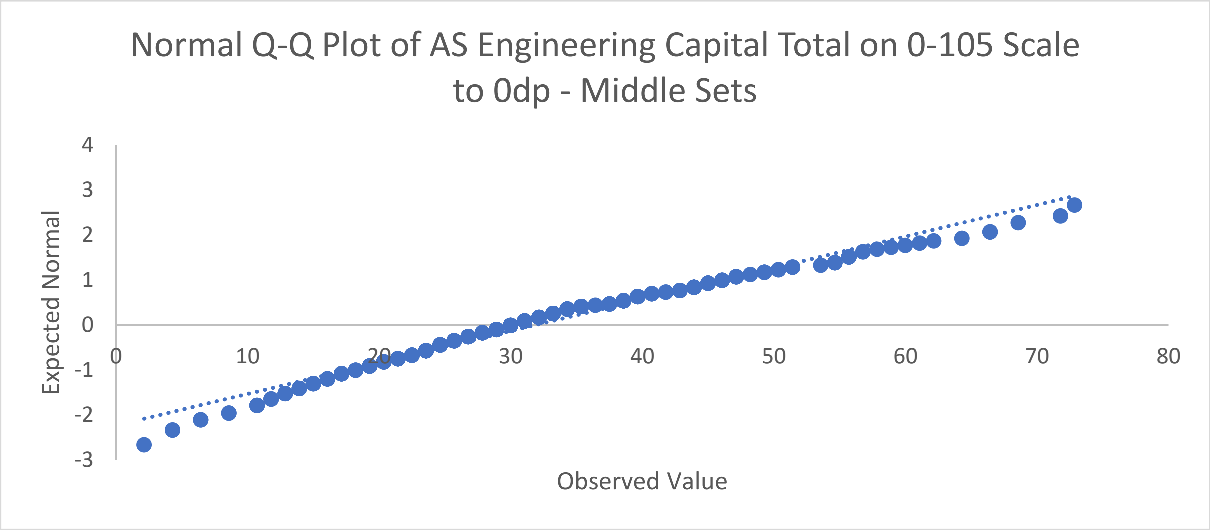
		Cases					
		Valid		Missing		Total	
	25.1.a. Science	N	Percent	N	Percent	N	Percent
AS Engineering Capital Total on 0-105 Scale to 0dp	There are not sets at this school/for this subject	183	100.0%	0	0.0%	183	100.0%
	Top	407	100.0%	0	0.0%	407	100.0%
	Middle	259	100.0%	0	0.0%	259	100.0%
	Bottom	48	100.0%	0	0.0%	48	100.0%

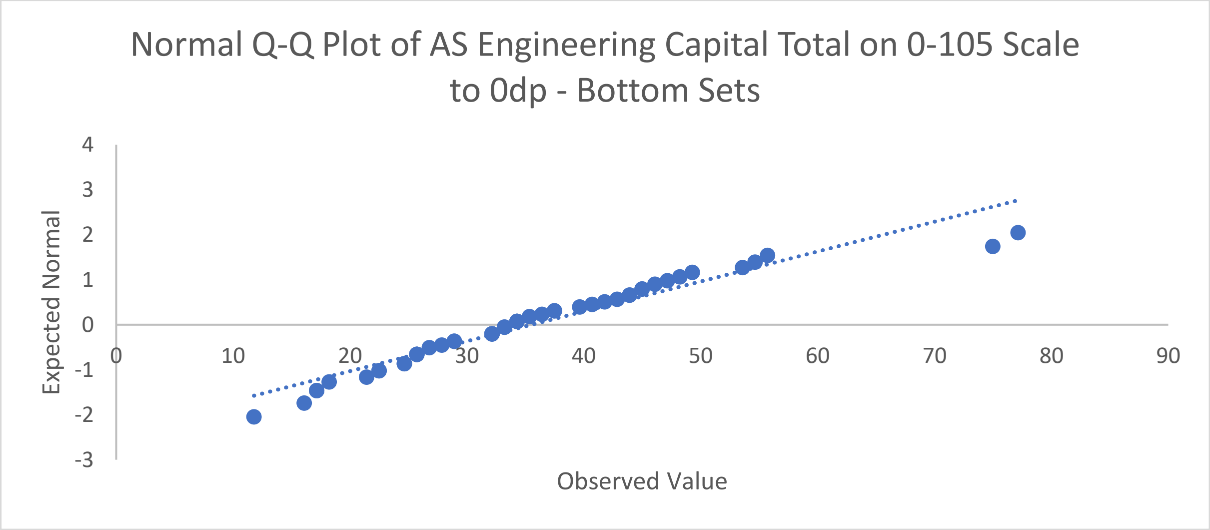
Descriptives

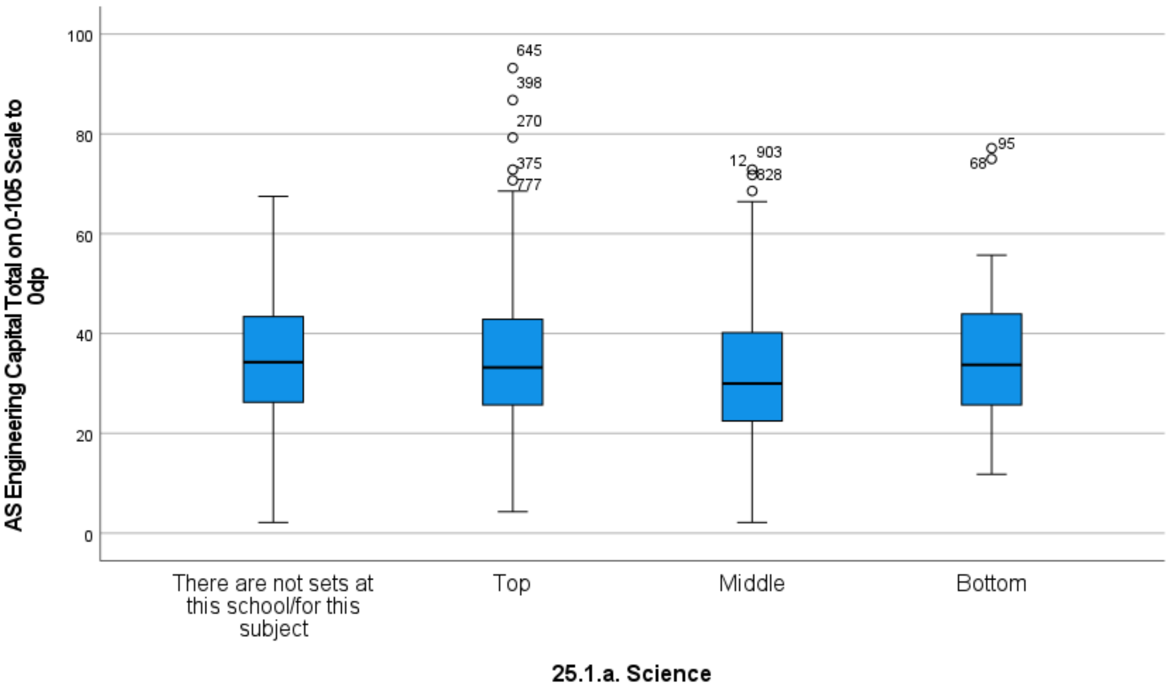
			25.1.a. Science							
			There are not sets at this school/for this subject		Top		Middle		Bottom	
			Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error
AS Engineering Capital Total on 0-105 Scale to 0dp	Mean		34.98	.941	35.06	.674	31.92	.863	35.54	1.976
	95% Confidence Interval for Mean	Lower Bound	33.12		33.74		30.22		31.56	
		Upper Bound	36.83		36.39		33.62		39.51	
	5% Trimmed Mean		34.90		34.59		31.45		34.64	
	Median		34.29		33.21		30.00		33.75	
	Variance		162.076		185.140		192.807		187.500	
	Std. Deviation		12.731		13.607		13.885		13.693	
	Minimum		2		4		2		12	
	Maximum		67		93		73		77	
	Range		65		89		71		65	
	Interquartile Range		18		17		18		18	
	Skewness		.125	.180	.652	.121	.537	.151	.966	.343
	Kurtosis		-.087	.357	.962	.241	.020	.302	1.549	.674




Normal Q-Q Plot of AS Engineering Capital Total on 0-105 Scale to 0dp - Top Sets


Normal Q-Q Plot of AS Engineering Capital Total on 0-105 Scale to 0dp - Middle Sets


Normal Q-Q Plot of AS Engineering Capital Total on 0-105 Scale to 0dp - Bottom Sets


AS Engineering Capital Total on 0-105 Scale to 0dp
100
80
60
40
20
0
645
398
270
375
777
12
903
828
95
68
There are not sets at this school/for this subject
Top
Middle
Bottom
25.1.a. Science

A one-way ANOVA was adopted to determine whether Archer-style engineering capital scores differed between groups based on school science academic sets. A total of 897 participants were classified into four groups: Top Sets (N=407), Middle Sets (N=259), Bottom Sets (N=48) and No Sets for this Subject (N=183). Archer-style engineering capital scores were found to statistically differ (F(3, 893) = 3.367, p=0.018, ETA2=0.011). Tukey post-hoc testing revealed only a single significant difference between the Top Sets and Middle Sets groups. The ETA^2 size of 0.011 indicates only a small effect of academic set in shaping Archer-style engineering capital scores.

Descriptives

AS Engineering Capital Total on 0-105 Scale

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
There are not sets at this school/for this subject	183	34.98	12.731	.941	33.12	36.83	2	67
Top	407	35.06	13.607	.674	33.74	36.39	4	93
Middle	259	31.92	13.885	.863	30.22	33.62	2	73
Bottom	48	35.54	13.693	1.976	31.56	39.51	12	77
Total	897	34.16	13.573	.453	33.27	35.05	2	93

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
AS Engineering Capital Total on 0-105 Scale	Based on Mean	.439	3	893	.725
	Based on Median	.321	3	893	.810
	Based on Median and with adjusted df	.321	3	883.956	.810
	Based on trimmed mean	.395	3	893	.757

ANOVA

AS Engineering Capital Total on 0-105 Scale

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1846.324	3	615.441	3.367	.018
Within Groups	163221.483	893	182.779		
Total	165067.808	896			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
AS Engineering Capital Total on 0-105 Scale	Eta-squared	.011	.000	.026
	Epsilon-squared	.008	-.003	.023
	Omega-squared Fixed-effect	.008	-.003	.023
	Omega-squared Random-effect	.003	-.001	.008

Multiple Comparisons

Dependent Variable: AS Engineering Capital Total on 0-105 Scale

						95% Confidence Interval	
	(I) 25.1.a. Science	(J) 25.1.a. Science	Mean Difference (I-J)	Std. Error	Sig.	Lower Bound	Upper Bound
Tukey HSD	There are not sets at this school/for this subject	Top	-.088	1.203	1.000	-3.19	3.01
		Middle	3.057	1.306	.090	-.30	6.42
		Bottom	-.559	2.192	.994	-6.20	5.08
	Top	There are not sets at this school/for this subject	.088	1.203	1.000	-3.01	3.19
		Middle	3.145*	1.075	.018	.38	5.91
		Bottom	-.471	2.063	.996	-5.78	4.84
	Middle	There are not sets at this school/for this subject	-3.057	1.306	.090	-6.42	.30
		Top	-3.145*	1.075	.018	-5.91	-.38
		Bottom	-3.616	2.125	.323	-9.08	1.85
	Bottom	There are not sets at this school/for this subject	.559	2.192	.994	-5.08	6.20
		Top	.471	2.063	.996	-4.84	5.78
		Middle	3.616	2.125	.323	-1.85	9.08

*. The mean difference is significant at the 0.05 level.

One-Way ANOVA: Deprivation (Cultural Capital) Differences and Science Capital Scores

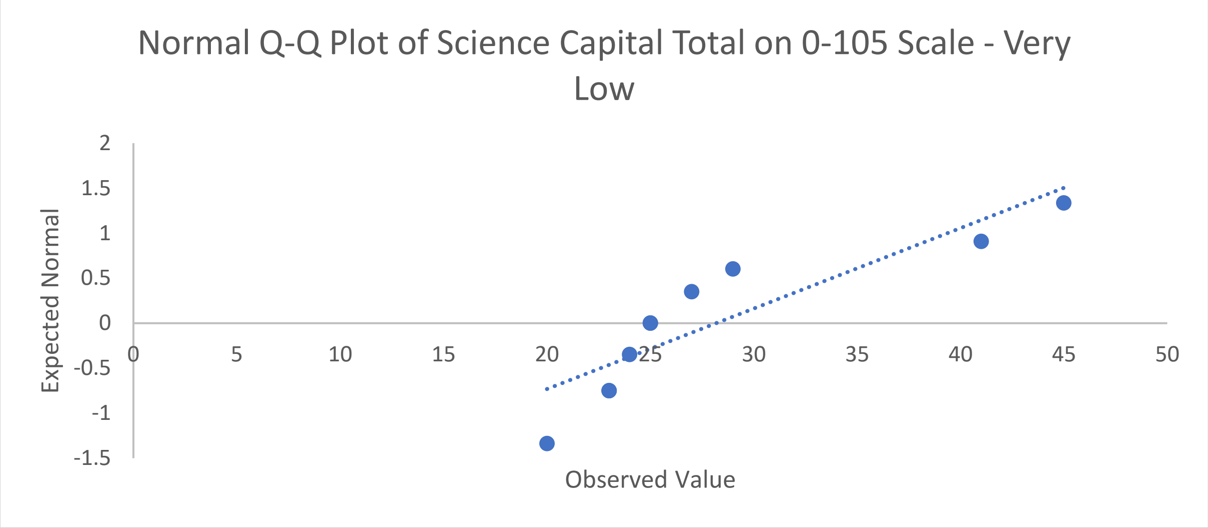
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be largely normally distributed with a robust Normal Q-Q plot and Skewness and Kurtosis values within the acceptable range of -1 to 1 – the Very Low group did express slightly greater kurtosis however this was deemed within an acceptable margin given the robustness of the ANOVA procedure. The assumptions underpinning this test were met approving its use.

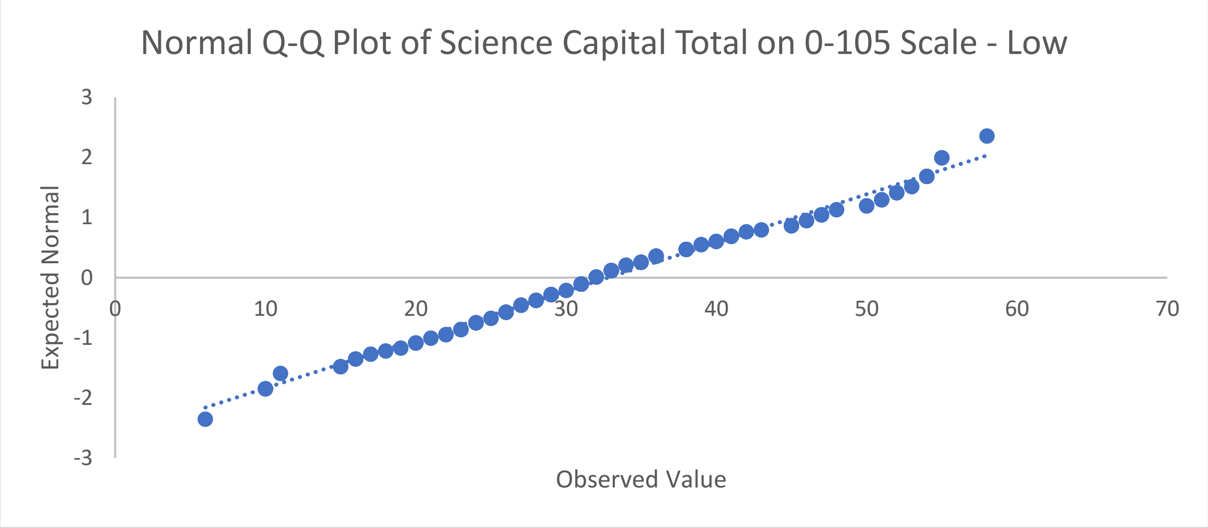
Case Processing Summary

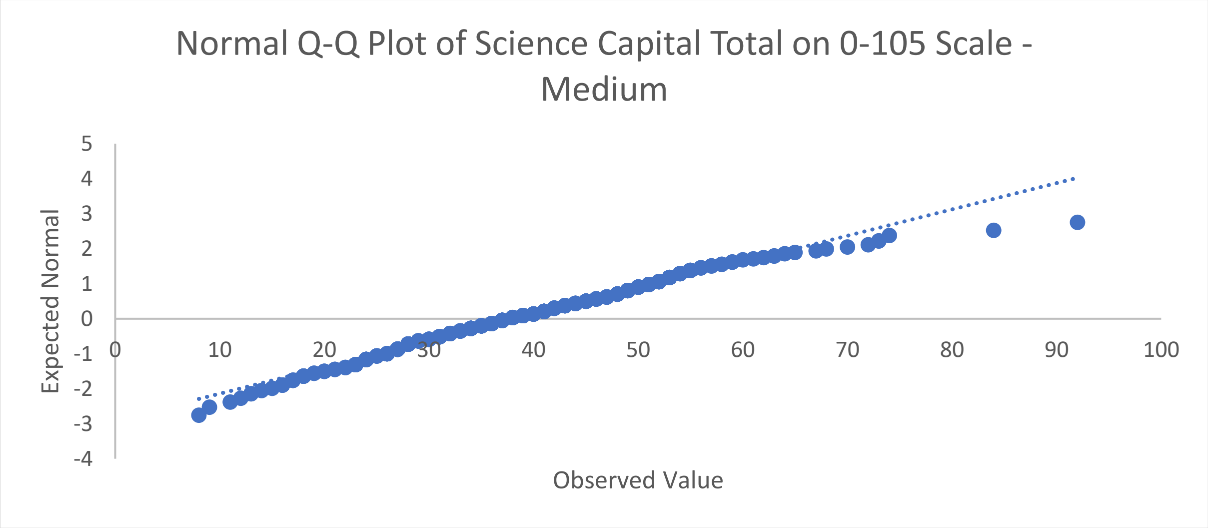
		Cases					
		Valid		Missing		Total	
	General Cultural Capital Category	N	Percent	N	Percent	N	Percent
Science Capital Total on 0-105 Scale	Very low	10	100.0%	0	0.0%	10	100.0%
	Low	107	100.0%	0	0.0%	107	100.0%
	Medium	343	100.0%	0	0.0%	343	100.0%
	High	296	100.0%	0	0.0%	296	100.0%
	Very high	165	100.0%	0	0.0%	165	100.0%

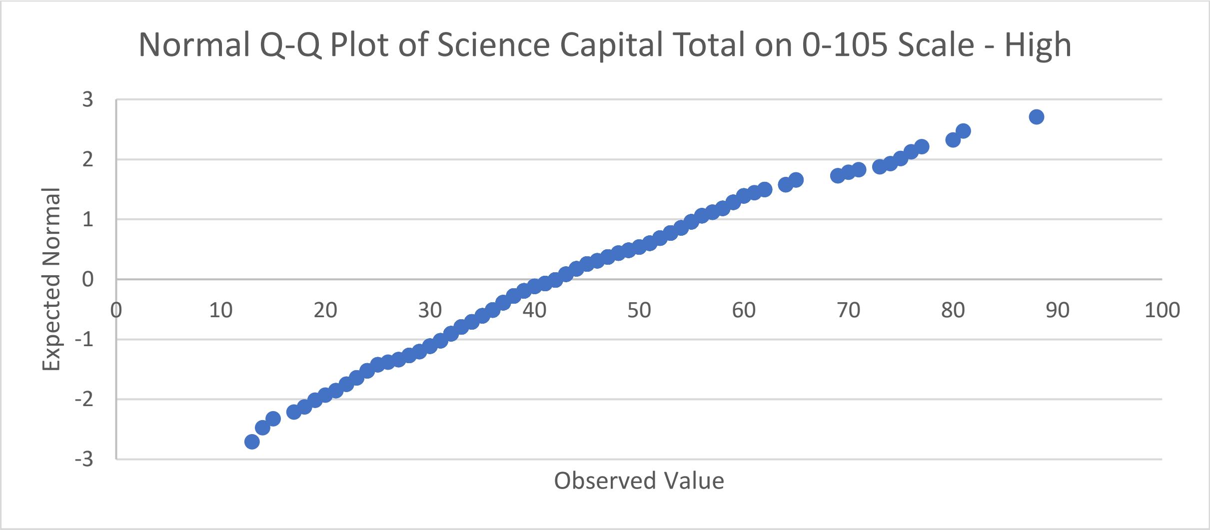
Descriptives

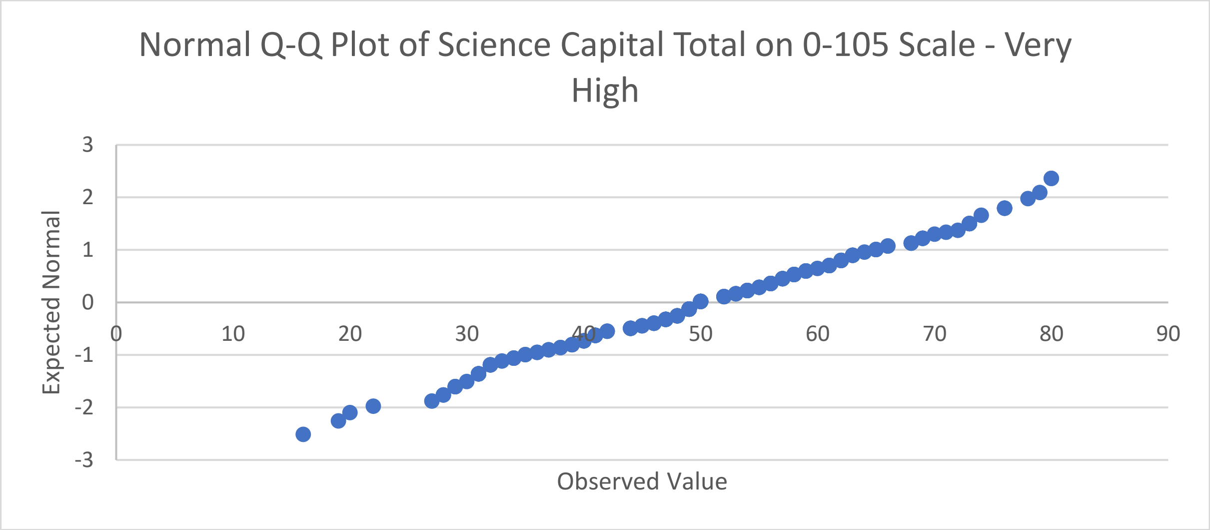
			General Cultural Capital Category									
			Very low		Low		Medium		High		Very high	
			Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error
Science Capital Total on 0-105 Scale	Mean		28.20	2.598	32.80	1.151	38.47	.703	43.05	.749	50.60	1.080
	95% Confidence Interval for Mean	Lower Bound	22.32		30.52		37.09		41.57		48.47	
		Upper Bound	34.08		35.09		39.85		44.52		52.73	
	5% Trimmed Mean		27.72		32.87		38.12		42.65		50.61	
	Median		25.00		32.00		37.00		42.00		50.00	
	Variance		67.511		141.706		169.320		166.160		192.388	
	Std. Deviation		8.217		11.904		13.012		12.890		13.870	
	Minimum		20		6		8		13		16	
	Maximum		45		58		92		88		80	
	Range		25		52		84		75		64	
	Interquartile Range		9		16		20		18		20	
	Skewness		1.469	.687	.068	.234	.464	.132	.459	.142	-.028	.189
	Kurtosis		1.072	1.334	-.497	.463	.669	.263	.404	.282	-.476	.376

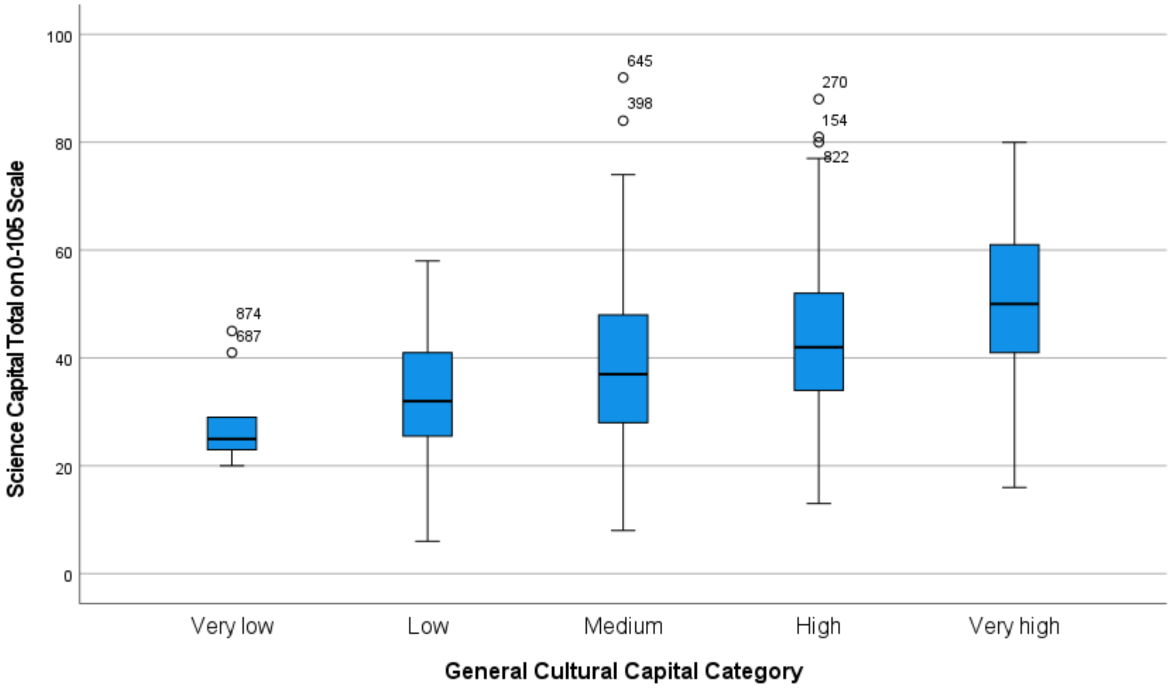

Normal Q-Q Plot of Science Capital Total on 0-105 Scale - Very Low
Expected Normal
2
1.5
1
0.5
0
-0.5
-1
-1.5
0
5
10
15
20
25
30
35
40
45
50
Observed Value


Normal Q-Q Plot of Science Capital Total on 0-105 Scale - Low
Expected Normal
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
Observed Value


Normal Q-Q Plot of Science Capital Total on 0-105 Scale - Medium
Expected Normal
5
4
3
2
1
0
-1
-2
-3
-4
0
10
20
30
40
50
60
70
80
90
100
Observed Value


Normal Q-Q Plot of Science Capital Total on 0-105 Scale - High


Normal Q-Q Plot of Science Capital Total on 0-105 Scale - Very High



A one-way ANOVA was adopted to determine whether science capital scores differed between groups based on general cultural capital. A total of 921 participants were classified into five groups based on cultural capital scores: Very Low (N=10), Low (N=107), Medium (N=343), High (N=296) and Very High (N=165). Science capital scores were found to statistically differ (F(4, 916) = 40.659, p<0.001, ETA^2=0.151). Tukey post-hoc testing revealed significant differences at all levels, except for those within the Very Low group (which was not strongly representative). The ETA^2 size of 0.151 indicates a strong effect of cultural capital in shaping science capital scores.

Descriptives

Science Capital Total on 0-105 Scale

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Very low	10	28.20	8.217	2.598	22.32	34.08	20	45
Low	107	32.80	11.904	1.151	30.52	35.09	6	58
Medium	343	38.47	13.012	.703	37.09	39.85	8	92
High	296	43.05	12.890	.749	41.57	44.52	13	88
Very high	165	50.60	13.870	1.080	48.47	52.73	16	80
Total	921	41.34	14.044	.463	40.44	42.25	6	92

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Science Capital Total on 0-105 Scale	Based on Mean	1.565	4	916	.182
	Based on Median	1.807	4	916	.125
	Based on Median and with adjusted df	1.807	4	911.040	.125
	Based on trimmed mean	1.624	4	916	.166

ANOVA

Science Capital Total on 0-105 Scale

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	27361.047	4	6840.262	40.659	<.001
Within Groups	154104.845	916	168.237		
Total	181465.891	920			

ANOVA Effect Sizes[a]

		Point Estimate	95% Confidence Interval	
			Lower	Upper
Science Capital Total on 0-105 Scale	Eta-squared	.151	.108	.190
	Epsilon-squared	.147	.104	.186
	Omega-squared Fixed-effect	.147	.104	.186
	Omega-squared Random-effect	.041	.028	.054

Multiple Comparisons

Dependent Variable: Science Capital Total on 0-105 Scale

	(I) General Cultural Capital Category	(J) General Cultural Capital Category	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Tukey HSD	Very low	Low	-4.604	4.289	.820	-16.33	7.12
		Medium	-10.269	4.161	.099	-21.64	1.10
		High	-14.847*	4.170	.004	-26.25	-3.45
		Very high	-22.400*	4.224	<.001	-33.95	-10.85
	Low	Very low	4.604	4.289	.820	-7.12	16.33
		Medium	-5.666*	1.436	<.001	-9.59	-1.74
		High	-10.244*	1.463	<.001	-14.24	-6.24
		Very high	-17.796*	1.610	<.001	-22.20	-13.40
	Medium	Very low	10.269	4.161	.099	-1.10	21.64
		Low	5.666*	1.436	<.001	1.74	9.59
		High	-4.578*	1.029	<.001	-7.39	-1.77
		Very high	-12.131*	1.229	<.001	-15.49	-8.77
	High	Very low	14.847*	4.170	.004	3.45	26.25
		Low	10.244*	1.463	<.001	6.24	14.24
		Medium	4.578*	1.029	<.001	1.77	7.39
		Very high	-7.553*	1.260	<.001	-11.00	-4.11
	Very high	Very low	22.400*	4.224	<.001	10.85	33.95
		Low	17.796*	1.610	<.001	13.40	22.20
		Medium	12.131*	1.229	<.001	8.77	15.49
		High	7.553*	1.260	<.001	4.11	11.00

*. The mean difference is significant at the 0.05 level.

One-Way ANOVA: Deprivation (Cultural Capital) Differences and Archer-Style Engineering Capital Scores

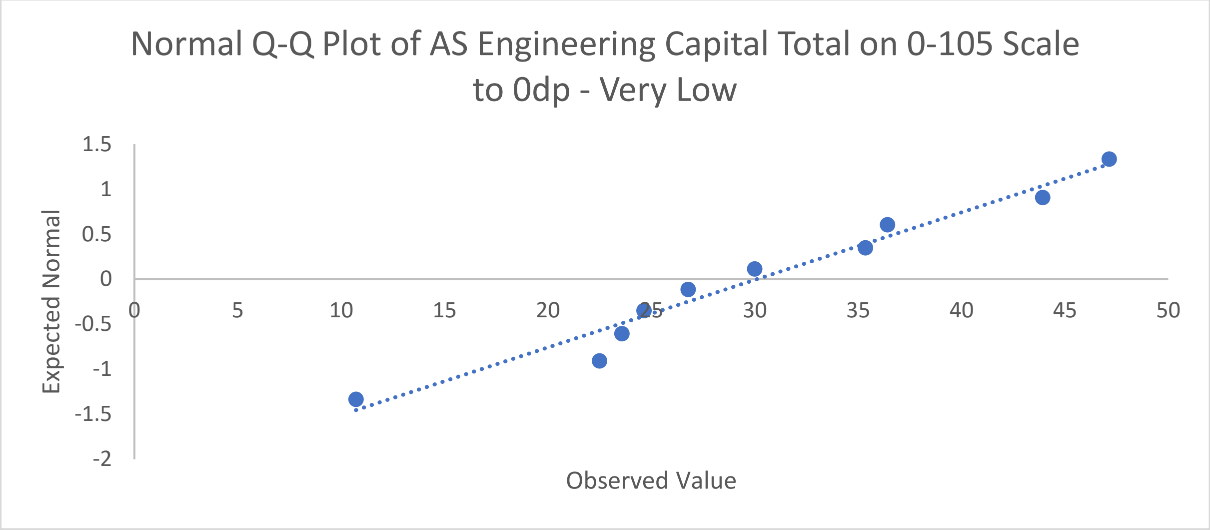
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be largely normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1 – the Medium group did exhibit a minor kurtosis but this was judged to be relatively minor. The assumptions underpinning this test were met approving its use.

Case Processing Summary

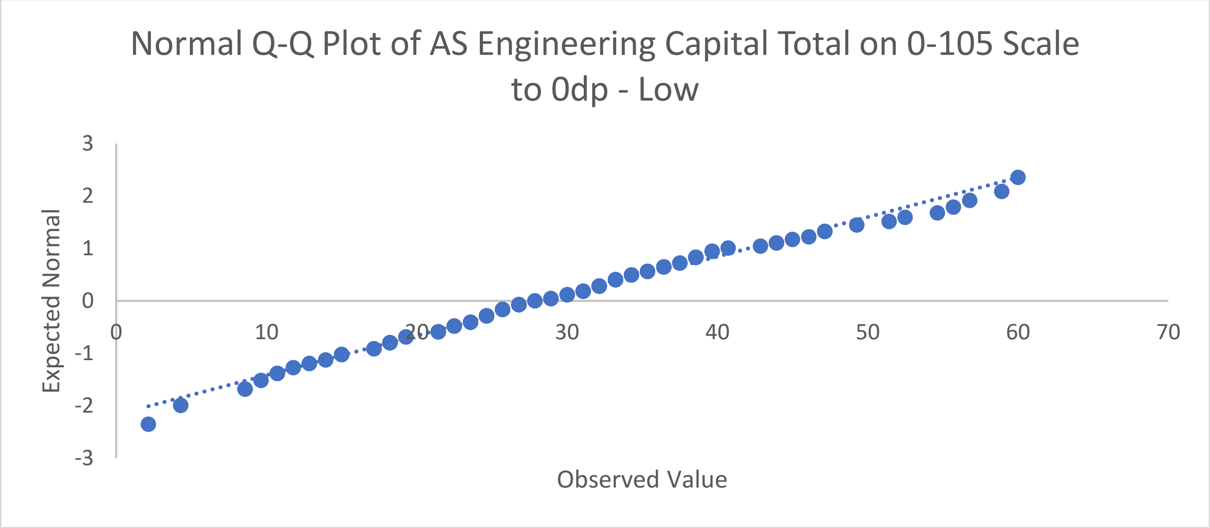
		Cases					
		Valid		Missing		Total	
	General Cultural Capital Category	N	Percent	N	Percent	N	Percent
AS Engineering Capital Total on 0-105 Scale to 0dp	Very low	10	100.0%	0	0.0%	10	100.0%
	Low	107	100.0%	0	0.0%	107	100.0%
	Medium	343	100.0%	0	0.0%	343	100.0%
	High	296	100.0%	0	0.0%	296	100.0%
	Very high	165	100.0%	0	0.0%	165	100.0%

Descriptives

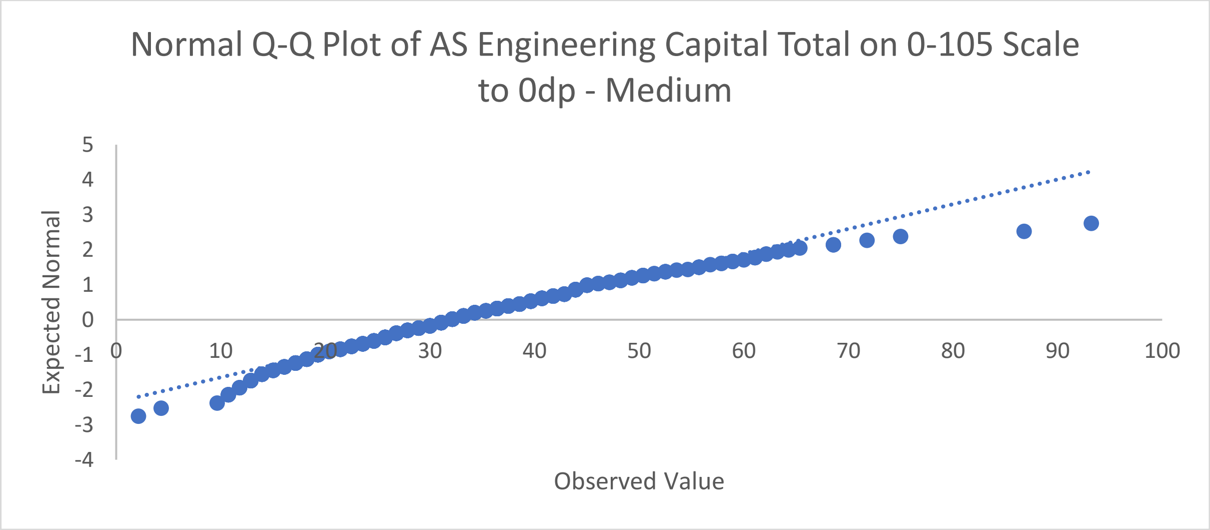
			General Cultural Capital Category									
			Very low		Low		Medium		High		Very high	
			Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error
AS Engineering Capital Total on 0-105 Scale to 0dp	Mean		30.11	3.442	28.80	1.233	33.30	.741	35.09	.750	37.86	1.049
	95% Confidence Interval for Mean	Lower Bound	22.32		26.35		31.84		33.62		35.79	
		Upper Bound	37.89		31.24		34.75		36.57		39.93	
	5% Trimmed Mean		30.24		28.52		32.66		34.78		37.65	
	Median		28.39		27.86		32.14		33.21		35.36	
	Variance		118.482		162.679		188.440		166.688		181.410	
	Std. Deviation		10.885		12.755		13.727		12.911		13.469	
	Minimum		11		2		2		4		6	
	Maximum		47		60		93		79		73	
	Range		36		58		91		75		66	
	Interquartile Range		15		17		18		18		19	
	Skewness		-.025	.687	.285	.234	.754	.132	.456	.142	.358	.189
	Kurtosis		-.131	1.334	-.217	.463	1.194	.263	.365	.282	-.135	.376



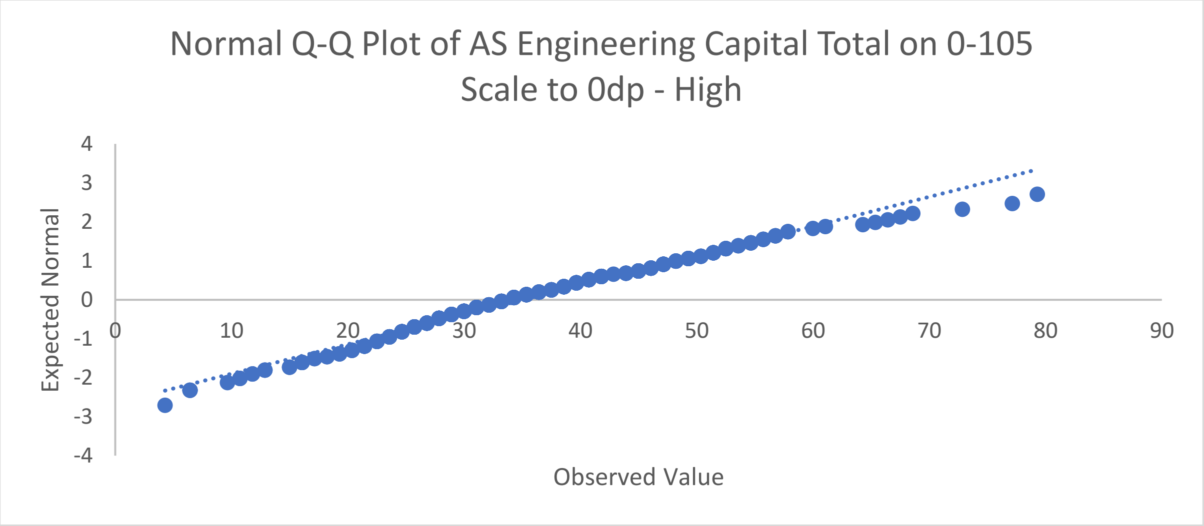
Normal Q-Q Plot of AS Engineering Capital Total on 0-105 Scale to 0dp - Very Low

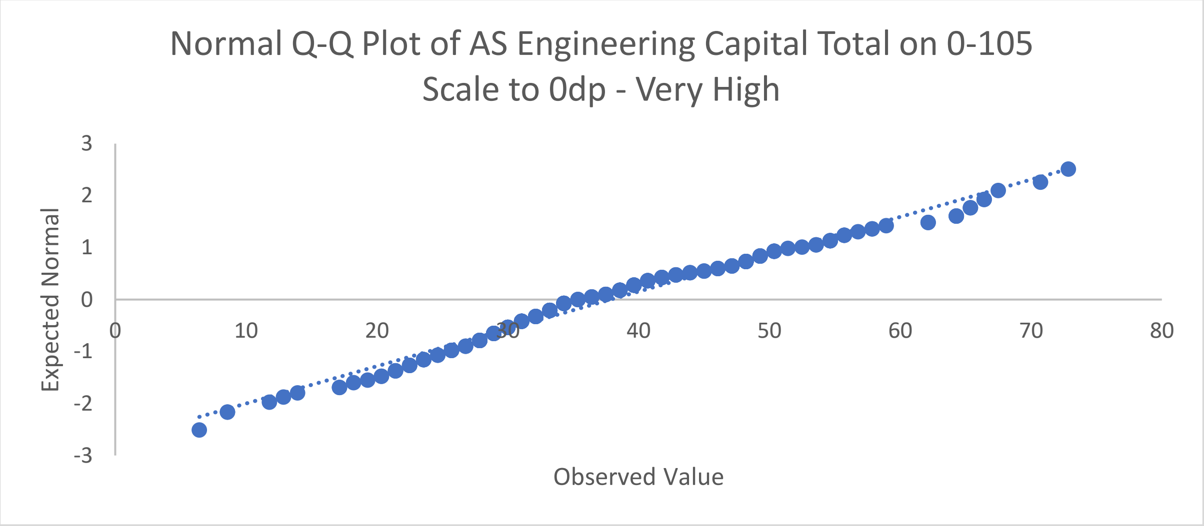


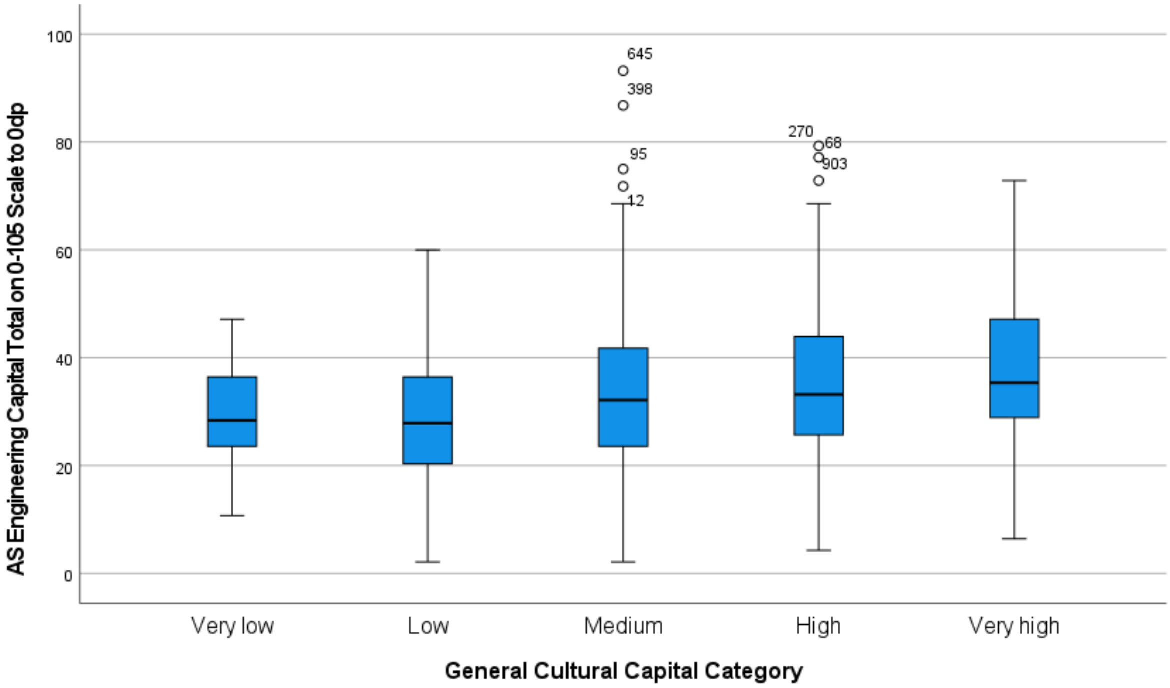
Normal Q-Q Plot of AS Engineering Capital Total on 0-105 Scale to 0dp - Low



Normal Q-Q Plot of AS Engineering Capital Total on 0-105 Scale to 0dp - Medium


Normal Q-Q Plot of AS Engineering Capital Total on 0-105 Scale to 0dp - High


Normal Q-Q Plot of AS Engineering Capital Total on 0-105 Scale to 0dp - Very High



A one-way ANOVA was adopted to determine whether Archer-style engineering capital scores differed between groups based on general cultural capital. A total of 921 participants were classified into five groups based on cultural capital scores: Very Low (N=10), Low (N=107), Medium (N=343), High (N=296) and Very High (N=165). Archer-style engineering capital scores were found to statistically differ (F(4, 916) = 8.511, p<0.001, ETA^2=0.036). Tukey post-hoc testing revealed significant differences between the Low & Medium groups, Low & High groups, Low & Very High groups, and Medium & Very High groups. The ETA^2 size of 0.036 indicates a weak-moderate effect of cultural capital group in shaping Archer-style engineering capital scores.

Descriptives

AS Engineering Capital Total on 0-105 Scale to 0dp

					95% Confidence Interval for Mean			
	N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound	Minimum	Maximum
Very low	10	30.11	10.885	3.442	22.32	37.89	11	47
Low	107	28.80	12.755	1.233	26.35	31.24	2	60
Medium	343	33.30	13.727	.741	31.84	34.75	2	93
High	296	35.09	12.911	.750	33.62	36.57	4	79
Very high	165	37.86	13.469	1.049	35.79	39.93	6	73
Total	921	34.13	13.501	.445	33.26	35.01	2	93

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
AS Engineering Capital Total on 0-105 Scale to 0dp	Based on Mean	.372	4	916	.829
	Based on Median	.317	4	916	.867
	Based on Median and with adjusted df	.317	4	908.263	.867
	Based on trimmed mean	.346	4	916	.847

ANOVA

AS Engineering Capital Total on 0-105 Scale to 0dp

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	6008.825	4	1502.206	8.511	<.001
Within Groups	161680.882	916	176.508		
Total	167689.707	920			

ANOVA Effect Sizes[a]

		Point Estimate	95% Confidence Interval	
			Lower	Upper
AS Engineering Capital Total on 0-105 Scale to 0dp	Eta-squared	.036	.013	.059
	Epsilon-squared	.032	.009	.055
	Omega-squared Fixed-effect	.032	.009	.055
	Omega-squared Random-effect	.008	.002	.014

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

Multiple Comparisons

Dependent Variable: AS Engineering Capital Total on 0-105 Scale to 0dp

	(I) General Cultural Capital Category	(J) General Cultural Capital Category	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Tukey HSD	Very low	Low	1.309	4.393	.998	-10.70	13.32
		Medium	-3.188	4.262	.945	-14.84	8.46
		High	-4.986	4.272	.770	-16.66	6.69
		Very high	-7.750	4.327	.379	-19.58	4.08
	Low	Very low	-1.309	4.393	.998	-13.32	10.70
		Medium	-4.497*	1.471	.019	-8.52	-.48
		High	-6.295*	1.499	<.001	-10.39	-2.20
		Very high	-9.059*	1.649	<.001	-13.57	-4.55
	Medium	Very low	3.188	4.262	.945	-8.46	14.84
		Low	4.497*	1.471	.019	.48	8.52
		High	-1.797	1.054	.431	-4.68	1.08
		Very high	-4.562*	1.259	.003	-8.00	-1.12
	High	Very low	4.986	4.272	.770	-6.69	16.66
		Low	6.295*	1.499	<.001	2.20	10.39
		Medium	1.797	1.054	.431	-1.08	4.68
		Very high	-2.764	1.291	.203	-6.29	.76
	Very high	Very low	7.750	4.327	.379	-4.08	19.58
		Low	9.059*	1.649	<.001	4.55	13.57
		Medium	4.562*	1.259	.003	1.12	8.00
		High	2.764	1.291	.203	-.76	6.29

*. The mean difference is significant at the 0.05 level.

One-Way ANOVA: Deprivation (IDACI) Differences and Science Capital Scores

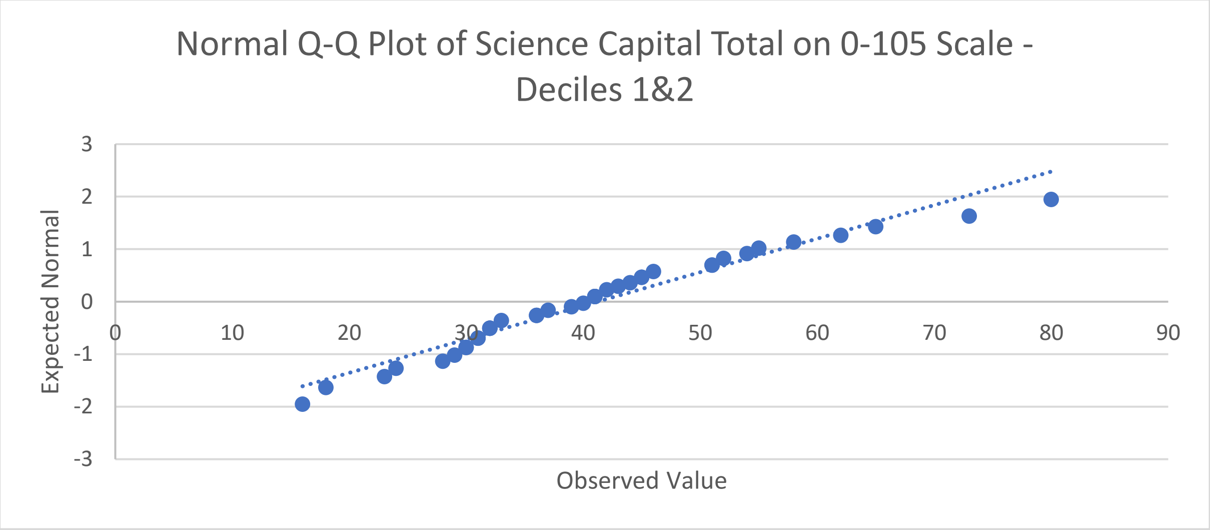
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be largely normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1. The assumptions underpinning this test were met approving its use.

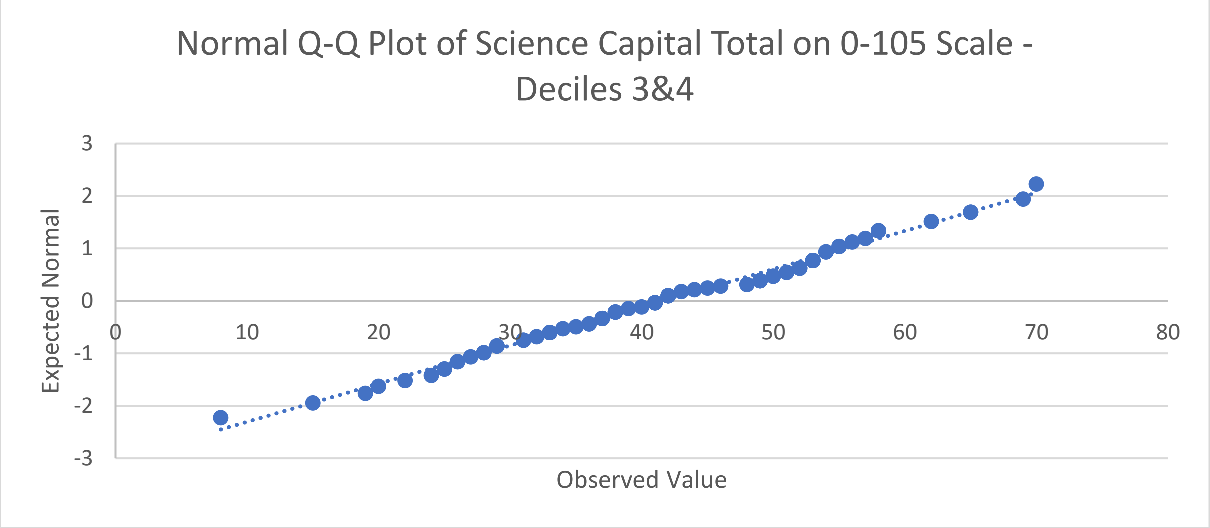
Case Processing Summary

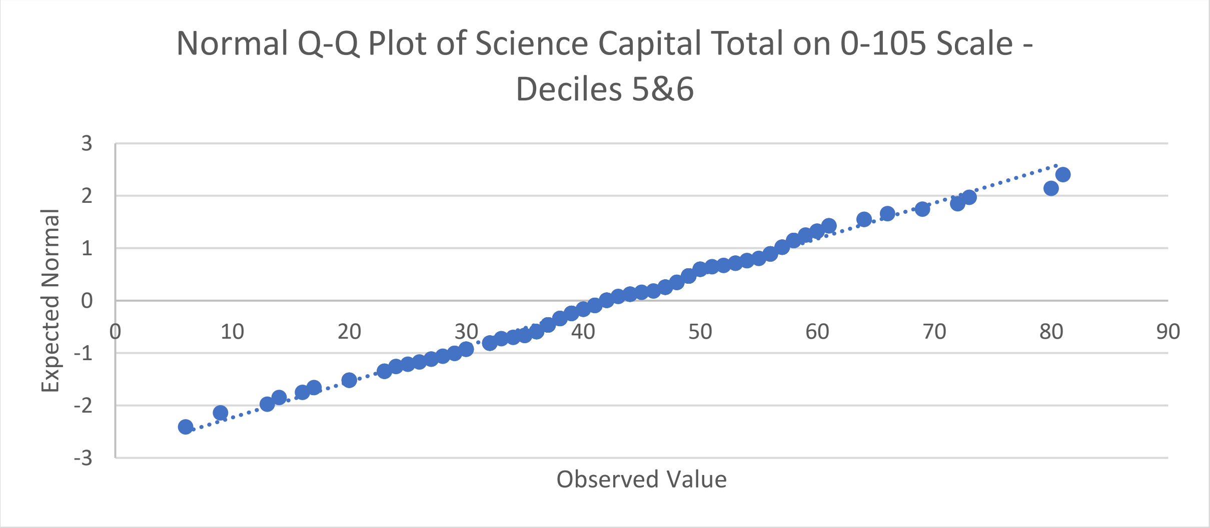
		Cases					
		Valid		Missing		Total	
	IDACI Decile	N	Percent	N	Percent	N	Percent
Science Capital Total on 0-105 Scale	1&2	38	100.0%	0	0.0%	38	100.0%
	3&4	76	100.0%	0	0.0%	76	100.0%
	5&6	123	100.0%	0	0.0%	123	100.0%
	7&8	219	100.0%	0	0.0%	219	100.0%
	9&10	150	100.0%	0	0.0%	150	100.0%

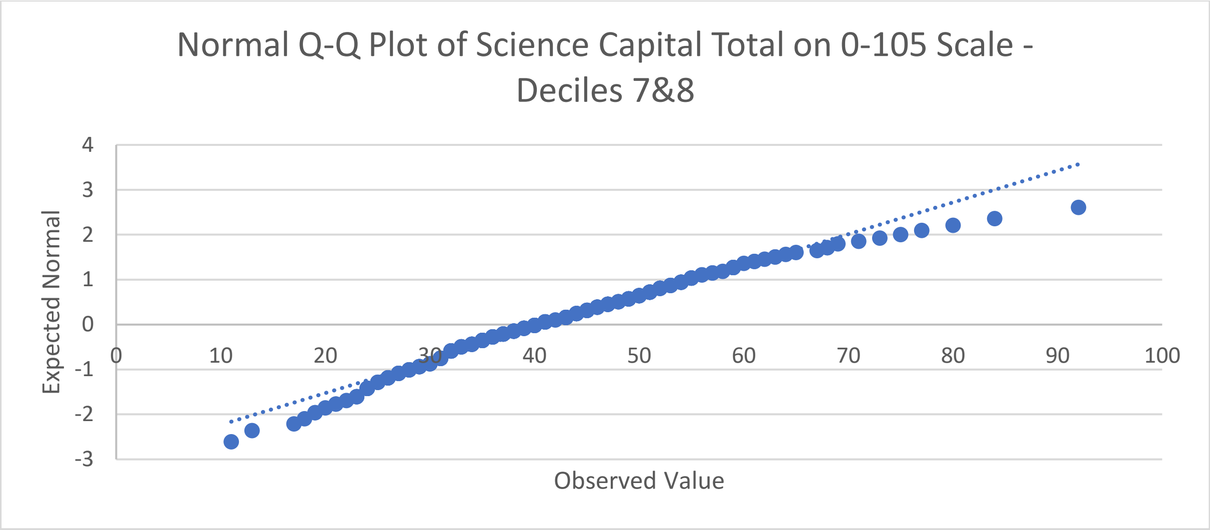
Descriptives

			IDACI Decile								
			1&2		3&4		5&6		7&8		9&10	
			Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error
Science Capital Total on 0-105 Scale	Mean		41.21	2.311	41.67	1.502	42.69	1.277	41.55	.925	42.23	1.233
	95% Confidence Interval for Mean	Lower Bound	36.53		38.68		40.16		39.73		39.79	
		Upper Bound	45.89		44.66		45.22		43.38		44.66	
	5% Trimmed Mean		40.59		41.71		42.66		40.98		41.95	
	Median		40.50		41.00		42.00		40.00		41.00	
	Variance		202.873		171.424		200.461		187.340		228.096	
	Std. Deviation		14.243		13.093		14.158		13.687		15.103	
	Minimum		16		8		6		11		10	
	Maximum		80		70		81		92		79	
	Range		64		62		75		81		69	
	Interquartile Range		20		21		17		19		22	
	Skewness		.728	.383	-.071	.276	.011	.218	.629	.164	.256	.198
	Kurtosis		.597	.750	-.381	.545	.228	.433	.596	.327	-.324	.394

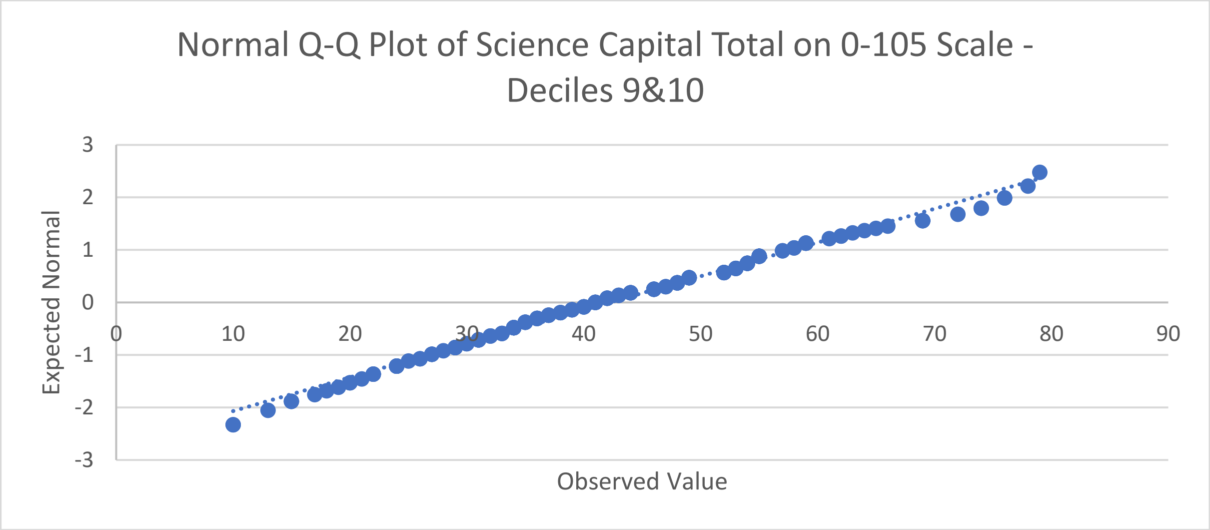

Normal Q-Q Plot of Science Capital Total on 0-105 Scale - Deciles 1&2


Normal Q-Q Plot of Science Capital Total on 0-105 Scale - Deciles 3&4

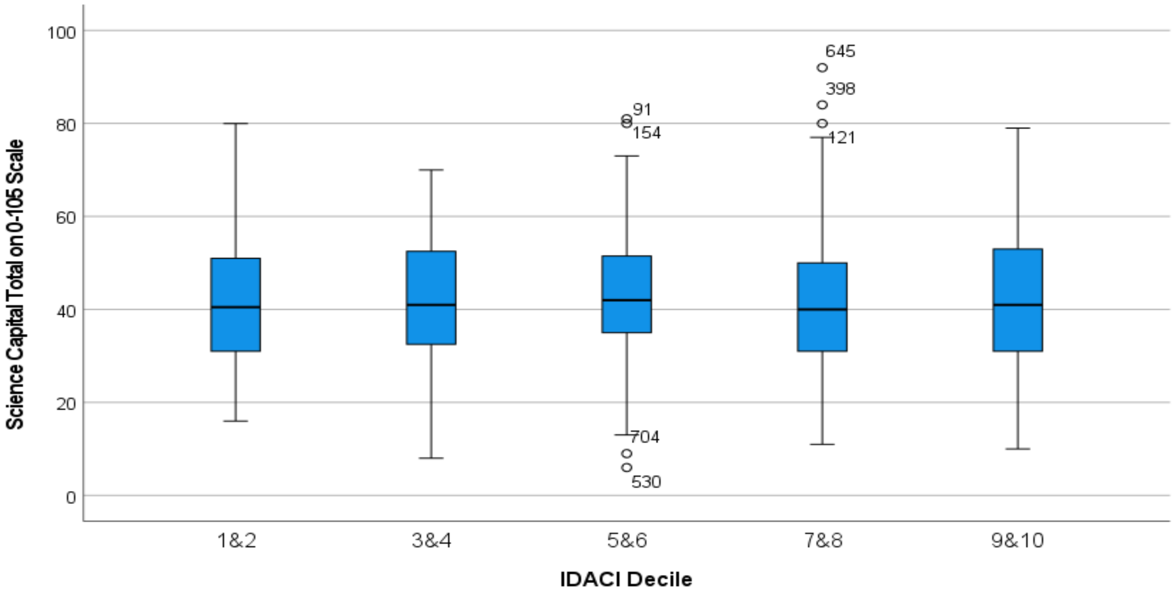

Normal Q-Q Plot of Science Capital Total on 0-105 Scale - Deciles 5&6



Normal Q-Q Plot of Science Capital Total on 0-105 Scale - Deciles 7&8



Normal Q-Q Plot of Science Capital Total on 0-105 Scale - Deciles 9&10



A one-way ANOVA was adopted to determine whether science capital scores differed between groups based on IDACI quintile. A total of 606 participants were classified into five groups based on IDACI quintiles: 1&2 (N=38), 3&4 (N=76), 5&6 (N=123), 7&8 (N=219), and 9&10 (N=150). Science capital scores were found to not significantly statistically differ (F(4, 601) = 0.176, p=0.951, ETA^2=0.001).

Descriptives

Science Capital Total on 0-105 Scale

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
12	38	41.21	14.243	2.311	36.53	45.89	16	80
34	76	41.67	13.093	1.502	38.68	44.66	8	70
56	123	42.69	14.158	1.277	40.16	45.22	6	81
78	219	41.55	13.687	.925	39.73	43.38	11	92
910	150	42.23	15.103	1.233	39.79	44.66	10	79
Total	606	41.94	14.071	.572	40.82	43.07	6	92

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Science Capital Total on 0-105 Scale	Based on Mean	.731	4	601	.571
	Based on Median	.685	4	601	.602
	Based on Median and with adjusted df	.685	4	594.737	.602
	Based on trimmed mean	.725	4	601	.575

ANOVA

Science Capital Total on 0-105 Scale

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	140.301	4	35.075	.176	.951
Within Groups	119645.792	601	199.078		
Total	119786.092	605			

One-Way ANOVA: Deprivation (IDACI) Differences and Archer-Style Engineering Capital Scores

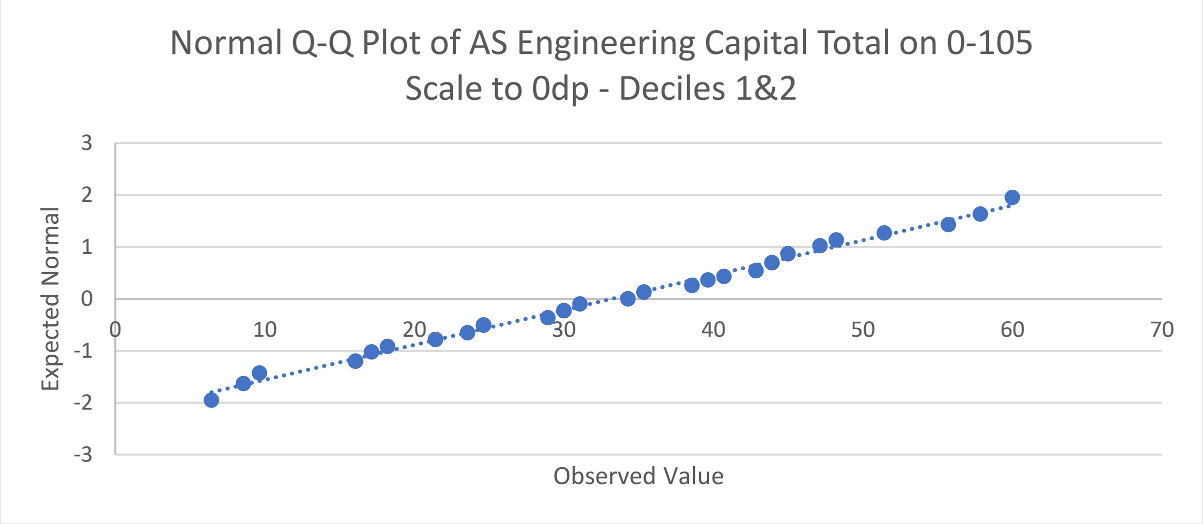
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A small number of outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be largely normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1 – the 7&8 group did exhibit a kurtosis, however all other groups were acceptable. The assumptions underpinning this test were met approving its use.

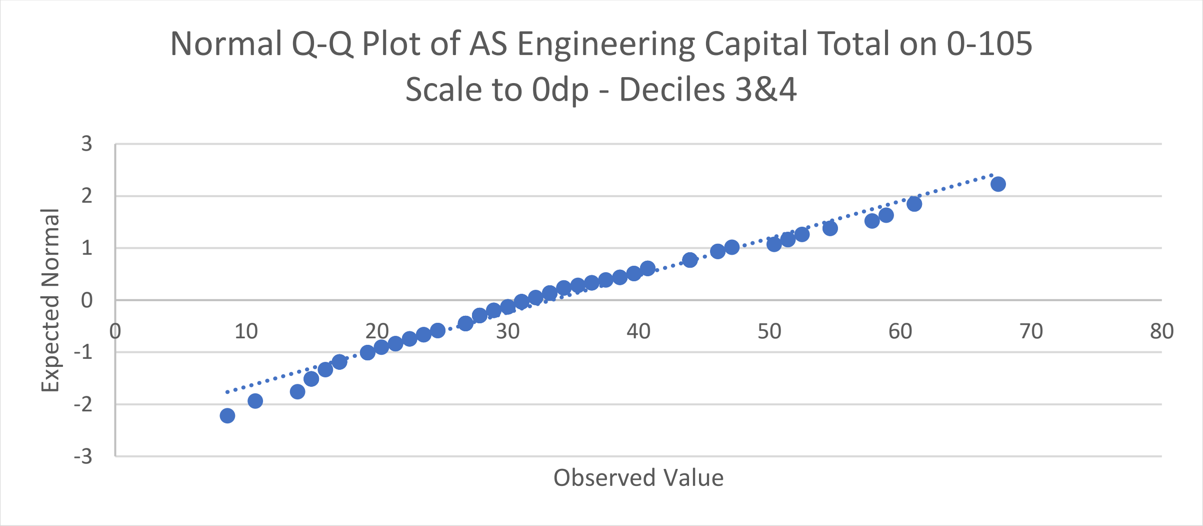
Case Processing Summary

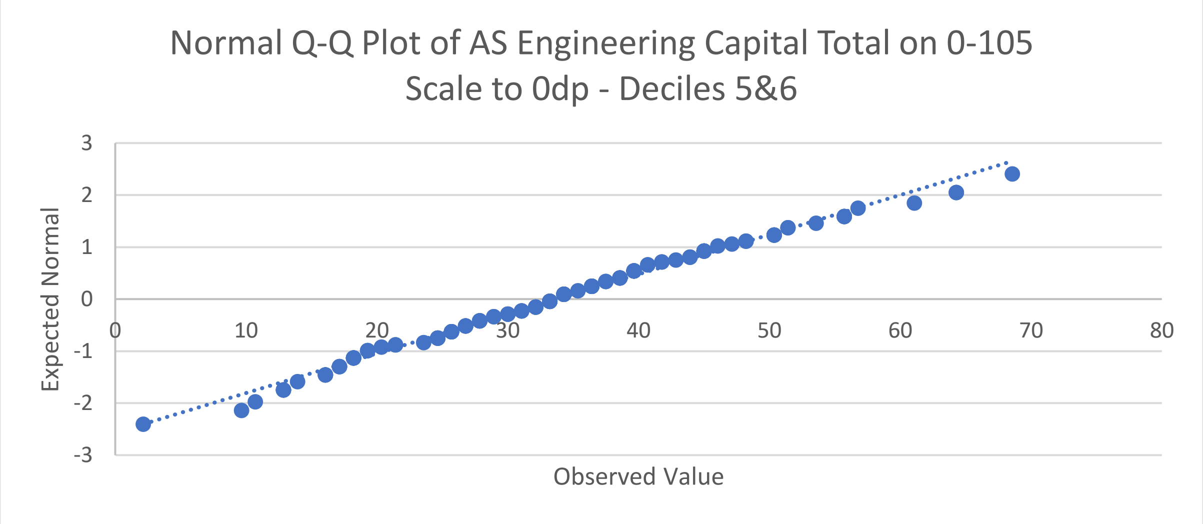
		Cases					
		Valid		Missing		Total	
	IDACI Decile	N	Percent	N	Percent	N	Percent
AS Engineering Capital Total on 0-105 Scale to 0dp	12	38	100.0%	0	0.0%	38	100.0%
	34	76	100.0%	0	0.0%	76	100.0%
	56	123	100.0%	0	0.0%	123	100.0%
	78	219	100.0%	0	0.0%	219	100.0%
	910	150	100.0%	0	0.0%	150	100.0%

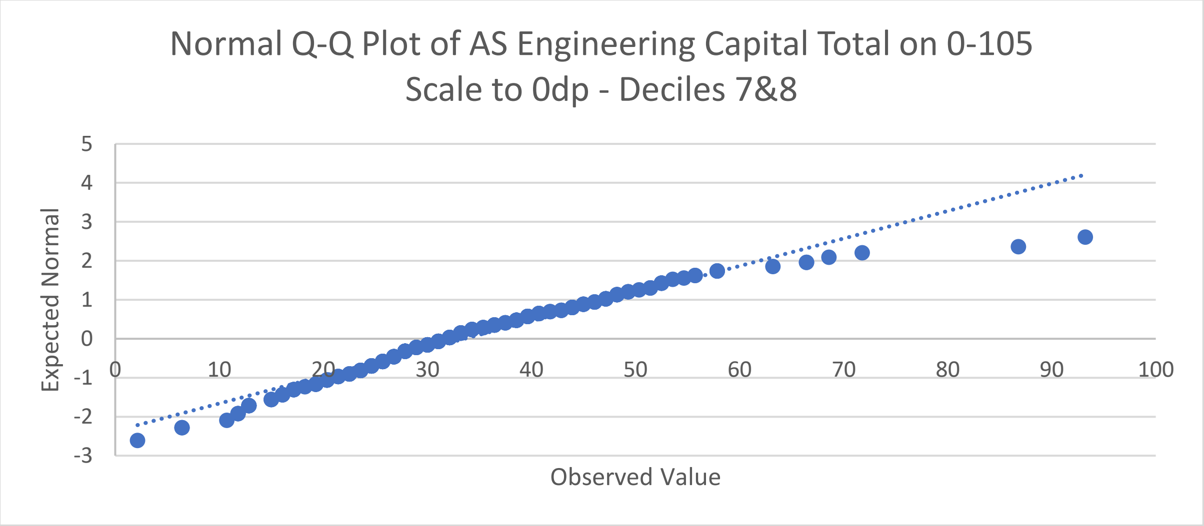
Descriptives

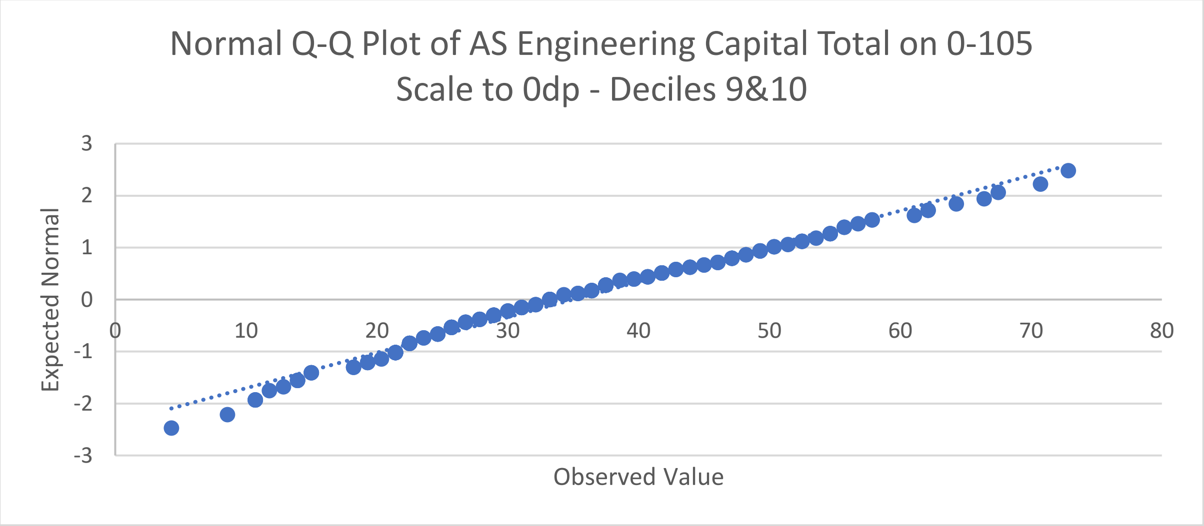
			IDACI Decile									
			1&2		3&4		5&6		7&8		9&10	
			Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error
AS Engineering Capital Total on 0-105 Scale to 0dp	Mean		33.24	2.237	33.34	1.524	33.72	1.143	33.54	.918	34.99	1.156
	95% Confidence Interval for Mean	Lower Bound	28.71		30.31		31.46		31.73		32.70	
		Upper Bound	37.78		36.38		35.98		35.35		37.27	
	5% Trimmed Mean		33.25		32.92		33.47		32.93		34.63	
	Median		34.29		31.07		33.21		32.14		33.21	
	Variance		190.219		176.417		160.702		184.371		200.561	
	Std. Deviation		13.792		13.282		12.677		13.578		14.162	
	Minimum		6		9		2		2		4	
	Maximum		60		67		69		93		73	
	Range		54		59		66		91		69	
	Interquartile Range		21		20		15		16		21	
	Skewness		-.060	.383	.464	.276	.247	.218	.902	.164	.381	.198
	Kurtosis		-.647	.750	-.332	.545	-.027	.433	2.064	.327	-.316	.394

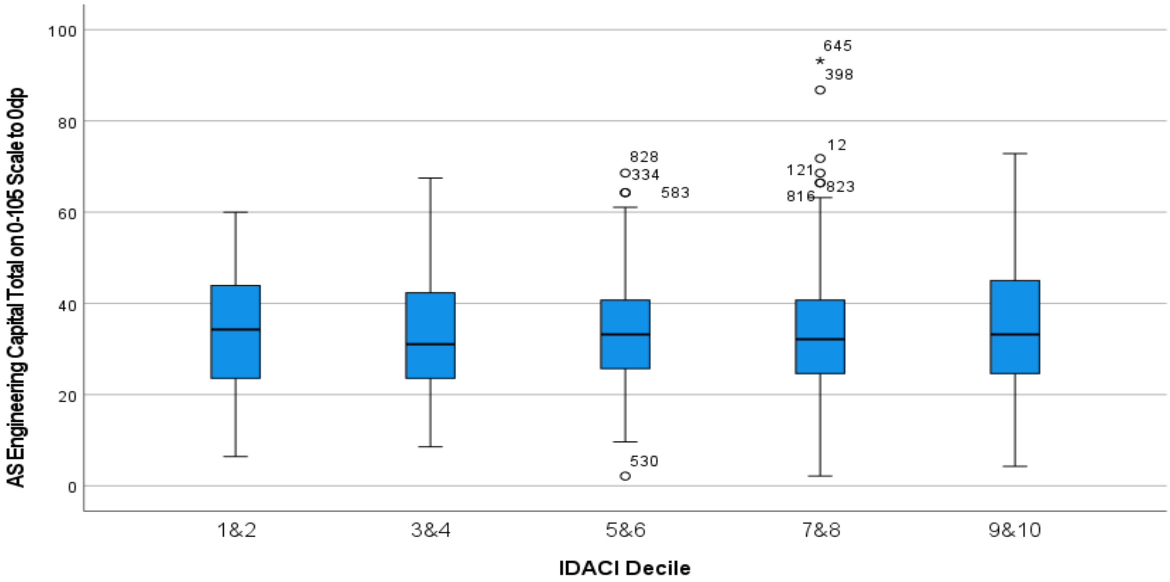

Normal Q-Q Plot of AS Engineering Capital Total on 0-105 Scale to 0dp - Deciles 1&2
Expected Normal
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
Observed Value


Normal Q-Q Plot of AS Engineering Capital Total on 0-105 Scale to 0dp - Deciles 3&4
Expected Normal
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
Observed Value


Normal Q-Q Plot of AS Engineering Capital Total on 0-105 Scale to 0dp - Deciles 5&6
Expected Normal
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
Observed Value


Normal Q-Q Plot of AS Engineering Capital Total on 0-105 Scale to 0dp - Deciles 7&8


Normal Q-Q Plot of AS Engineering Capital Total on 0-105 Scale to 0dp - Deciles 9&10



A one-way ANOVA was adopted to determine whether Archer-style engineering capital scores differed between groups based on IDACI quintile. A total of 606 participants were classified into five groups based on IDACI quintiles:1&2 (N=38), 3&4 (N=76), 5&6 (N=123), 7&8 (N=219), and 9&10 (N=150). Archer-style engineering capital scores were found to not statistically differ (F(4,601) = 0.340, p=0.851, ETA^2=0.002).

Descriptives

AS Engineering Capital Total on 0-105 Scale to 0dp

					95% Confidence Interval for Mean			
	N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound	Minimum	Maximum
12	38	33.24	13.792	2.237	28.71	37.78	6	60
34	76	33.34	13.282	1.524	30.31	36.38	9	67
56	123	33.72	12.677	1.143	31.46	35.98	2	69
78	219	33.54	13.578	.918	31.73	35.35	2	93
910	150	34.99	14.162	1.156	32.70	37.27	4	73
Total	606	33.89	13.496	.548	32.81	34.97	2	93

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
AS Engineering Capital Total on 0-105 Scale to 0dp	Based on Mean	.771	4	601	.544
	Based on Median	.672	4	601	.612
	Based on Median and with adjusted df	.672	4	593.816	.612
	Based on trimmed mean	.774	4	601	.543

ANOVA

AS Engineering Capital Total on 0-105 Scale to 0dp

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	248.998	4	62.250	.340	.851
Within Groups	109951.570	601	182.948		
Total	110200.568	605			

Independent Samples T-Test: Nation and Science Capital Scores

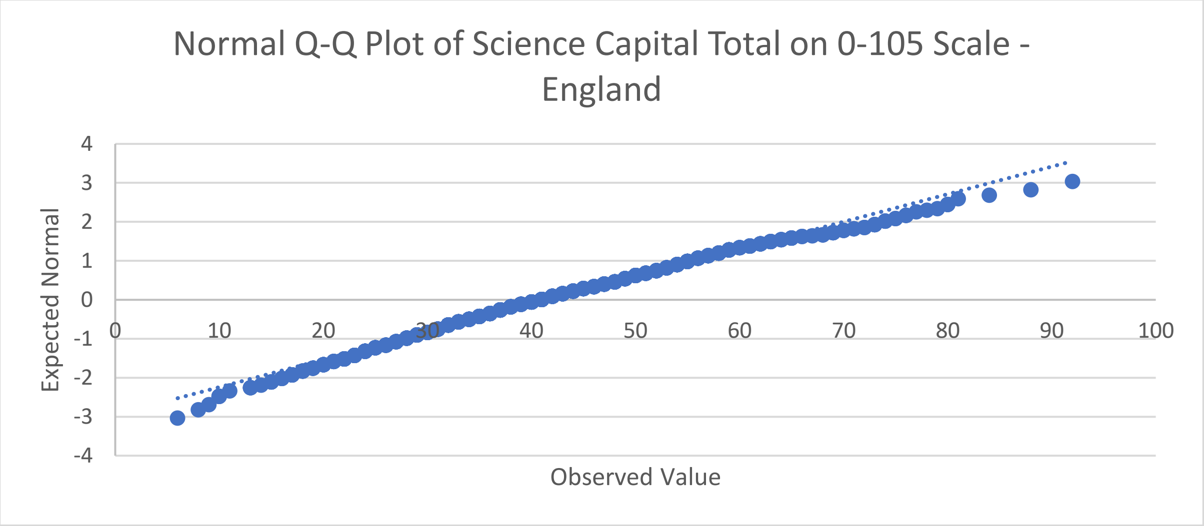
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1. The assumptions underpinning this test were met approving its use.

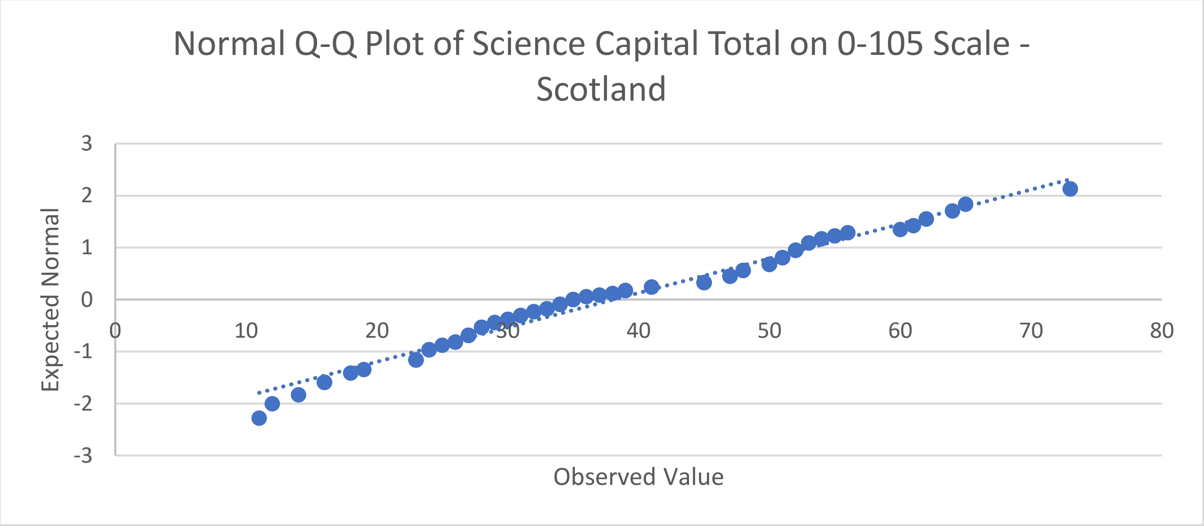
Case Processing Summary

		Cases					
		Valid		Missing		Total	
	Nation	N	Percent	N	Percent	N	Percent
Science Capital Total on 0-105 Scale	England	832	100.0%	0	0.0%	832	100.0%
	Scotland	89	100.0%	0	0.0%	89	100.0%

Descriptives

			Nation			
			England		Scotland	
			Statistic	Std. Error	Statistic	Std. Error
Science Capital Total on 0-105 Scale	Mean		41.69	.485	38.08	1.519
	95% Confidence Interval for Mean	Lower Bound	40.74		35.06	
		Upper Bound	42.64		41.10	
	5% Trimmed Mean		41.33		37.78	
	Median		41.00		35.00	
	Variance		195.361		205.346	
	Std. Deviation		13.977		14.330	
	Minimum		6		11	
	Maximum		92		73	
	Range		86		62	
	Interquartile Range		19		23	
	Skewness		.365	.085	.311	.255
	Kurtosis		.143	.169	-.571	.506


Normal Q-Q Plot of Science Capital Total on 0-105 Scale - England
Expected Normal
4
3
2
1
0
-1
-2
-3
-4
0
10
20
30
40
50
60
70
80
90
100
Observed Value


Normal Q-Q Plot of Science Capital Total on 0-105 Scale - Scotland
Expected Normal
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
Observed Value

A Student's independent samples t-test identified a significant difference in the science capital scores of young people in England (M=41.69, SD=13.98) and Scotland (M=38.08, SD=14.33) (t(919)=2.313, p=0.021, d=0.258).The Cohen's d effect size highlights a weak effect of national setting on science capital scores.

Group Statistics

	Nation	N	Mean	Std. Deviation	Std. Error Mean
Science Capital Total on 0-105 Scale	England	832	41.69	13.977	.485
	Scotland	89	38.08	14.330	1.519

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Science Capital Total on 0-105 Scale	Equal variances assumed	1.102	.294	2.313	919	.010	.021	3.615	1.563	.548	6.682
	Equal variances not assumed			2.267	106.706	.013	.025	3.615	1.594	.454	6.776

Independent Samples Effect Sizes

				95% Confidence Interval	
		Standardizer[a]	Point Estimate	Lower	Upper
Science Capital Total on 0-105 Scale	Cohen's d	14.011	.258	.039	.477
	Hedges' correction	14.023	.258	.039	.476
	Glass's delta	14.330	.252	.030	.473

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

Independent Samples T-Test: Nation and Archer-Style Engineering Capital Scores

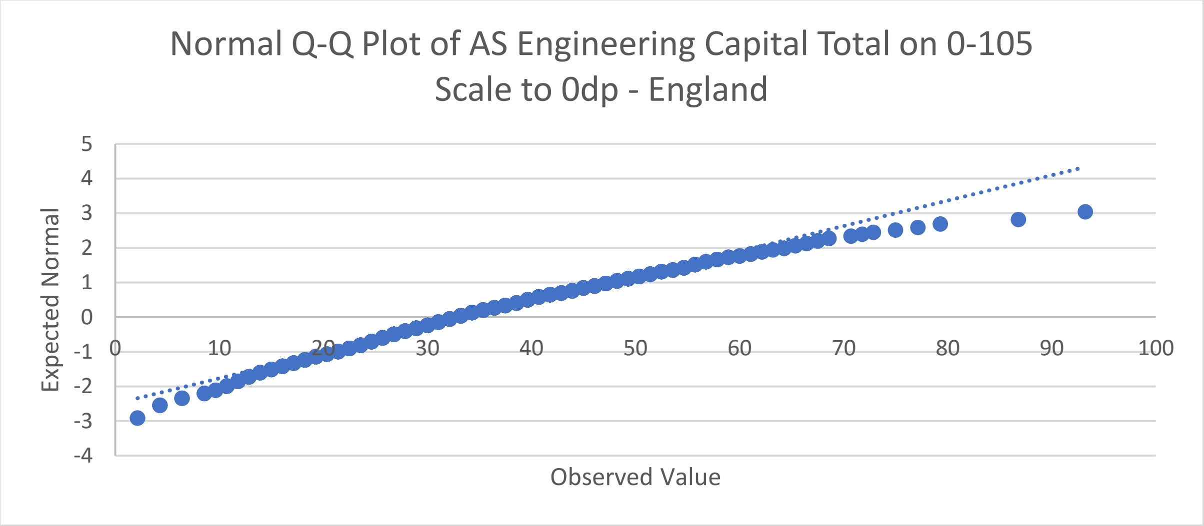
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1. The assumptions underpinning this test were met approving its use.

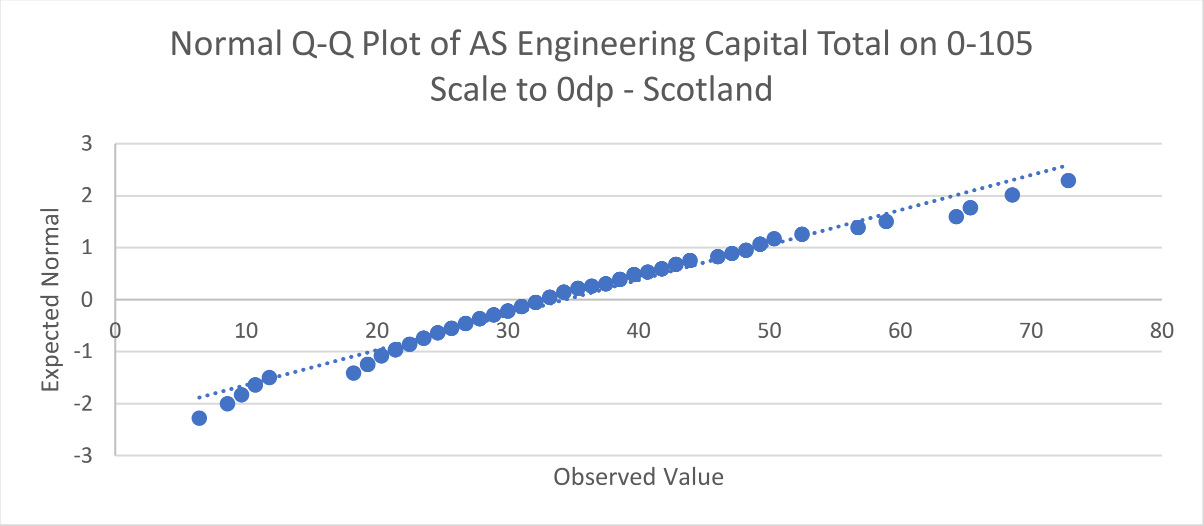
Case Processing Summary

		Cases					
		Valid		Missing		Total	
	Nation	N	Percent	N	Percent	N	Percent
AS Engineering Capital Total on 0-105 Scale to 0dp	England	832	100.0%	0	0.0%	832	100.0%
	Scotland	89	100.0%	0	0.0%	89	100.0%

Descriptives

			Nation			
			England		Scotland	
			Statistic	Std. Error	Statistic	Std. Error
AS Engineering Capital Total on 0-105 Scale to 0dp	Mean		34.10	.466	34.43	1.497
	95% Confidence Interval for Mean	Lower Bound	33.19		31.46	
		Upper Bound	35.02		37.40	
	5% Trimmed Mean		33.70		34.00	
	Median		33.21		33.21	
	Variance		180.671		199.359	
	Std. Deviation		13.441		14.119	
	Minimum		2		6	
	Maximum		93		73	
	Range		91		66	
	Interquartile Range		18		19	
	Skewness		.519	.085	.504	.255
	Kurtosis		.554	.169	.125	.506


Normal Q-Q Plot of AS Engineering Capital Total on 0-105 Scale to 0dp - England
Expected Normal
5
4
3
2
1
0
-1
-2
-3
-4
0
10
20
30
40
50
60
70
80
90
100
Observed Value


Normal Q-Q Plot of AS Engineering Capital Total on 0-105 Scale to 0dp - Scotland
Expected Normal
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
Observed Value

A Student’s independent samples t-test identified no significant difference in the Archer-style engineering capital scores of young people in England (M=34.10, SD=13.44) and Scotland (M=34.43, SD=14.12) (t(919)=-0.218, p=0.827, d=-0.024).

Group Statistics

	Nation	N	Mean	Std. Deviation	Std. Error Mean
AS Engineering Capital Total on 0-105 Scale to 0dp	England	832	34.10	13.441	.466
	Scotland	89	34.43	14.119	1.497

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
AS Engineering Capital Total on 0-105 Scale to 0dp	Equal variances assumed	.336	.562	-.218	919	.414	.827	-.329	1.506	-3.285	2.628
	Equal variances not assumed			-.210	105.784	.417	.834	-.329	1.568	-3.436	2.779

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
AS Engineering Capital Total on 0-105 Scale to 0dp	Cohen's d	13.508	-.024	-.243	.194
	Hedges' correction	13.519	-.024	-.243	.194
	Glass's delta	14.119	-.023	-.242	.195

a. The denominator used in estimating the effect sizes.

Cohen's d uses the pooled standard deviation.

Hedges' correction uses the pooled standard deviation, plus a correction factor.

Glass's delta uses the sample standard deviation of the control group.

Binary Logistic Regression: Engineering Educational Aspiration and Archer-Style Engineering Capital

A binary logistic regression was adopted to determine the effect of Archer-style engineering capital score on the likelihood of aspiring to engineering education. Statistical assumptions were tested and confirmed the linearity of the relationship between the IV and DV logit, a lack of significant multicollinearity and lack of influential outliers supporting the use of this procedure. The logistic regression model was statistically significant, χ2(1) = 219.683, p<0.001. The model explained 32.3% (Nagelkerke R^2) of the variance in educational aspiration and correctly classified 80.4% of cases. Sensitivity was 43.0%, specificity was 93.3%. Increasing Archer-style engineering capital score was associated with a greater likelihood of aspiring to engineering educational pathways.

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	887	96.3
	Missing Cases	34	3.7
	Total	921	100.0
Unselected Cases		0	.0
Total		921	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
No	0
Yes	1

Classification Table[a,b]

			Predicted		
			Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no		Percentage Correct
	Observed		No	Yes	
Step 0	Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no	No	659	0	100.0
		Yes	228	0	.0
	Overall Percentage				74.3

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-1.061	.077	190.826	1	<.001	.346

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	AS Engineering Capital Total on 0-105 Scale to 0dp	205.019	1	<.001
	Overall Statistics		205.019	1	<.001

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	219.683	1	<.001
	Block	219.683	1	<.001
	Model	219.683	1	<.001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	791.399[a]	.219	.323

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	6.798	8	.559

Classification Table[a]

			Predicted		
			Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no		Percentage Correct
	Observed		No	Yes	
Step 1	Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no	No	615	44	93.3
		Yes	130	98	43.0
	Overall Percentage				80.4

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	AS Engineering Capital Total on 0-105 Scale to 0dp	.098	.008	151.308	1	<.001	1.103	1.086	1.121
	Constant	-4.736	.327	209.936	1	<.001	.009		

a. Variable(s) entered on step 1: AS Engineering Capital Total on 0-105 Scale to 0dp.

Binary Logistic Regression: Engineering Educational Aspiration and Science Capital

A binary logistic regression was adopted to determine the effect of science capital score on the likelihood of aspiring to engineering education. Statistical assumptions were tested and confirmed the linearity of the relationship between the IV and DV logit, a lack of significant multicollinearity and lack of influential outliers supporting the use of this procedure. The logistic regression model was statistically significant, $\chi2(1) = 9.938$, $p=0.002$. The model explained 1.6% (Nagelkerke R^2) of the variance in educational aspiration and correctly classified 74.3% of cases. Sensitivity was 0.0%, specificity was 100.0%. Increasing science capital score was associated with a greater likelihood of aspiring to engineering educational pathways – however, notably this performance was poor for those who aspired to engineering education.

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	887	96.3
	Missing Cases	34	3.7
	Total	921	100.0
Unselected Cases		0	.0
Total		921	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
No	0
Yes	1

Classification Table[a,b]

			Predicted		
			Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no		Percentage Correct
	Observed		No	Yes	
Step 0	Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no	No	659	0	100.0
		Yes	228	0	.0
	Overall Percentage				74.3

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-1.061	.077	190.826	1	<.001	.346

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Science Capital Total on 0-105 Scale	10.009	1	.002
	Overall Statistics		10.009	1	.002

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	9.938	1	.002
	Block	9.938	1	.002
	Model	9.938	1	.002

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1001.144[a]	.011	.016

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	8.788	8	.360

Classification Table[a]

			Predicted		
			Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no		Percentage Correct
	Observed		No	Yes	
Step 1	Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no	No	659	0	100.0
		Yes	228	0	.0
	Overall Percentage				74.3

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Science Capital Total on 0-105 Scale	.017	.005	9.884	1	.002	1.017	1.006	1.028
	Constant	-1.790	.248	51.927	1	<.001	.167		

a. Variable(s) entered on step 1: Science Capital Total on 0-105 Scale.

Binary Logistic Regression: Engineering Educational Aspiration and General Cultural Capital

A binary logistic regression was adopted to determine the effect of general cultural capital score on the likelihood of aspiring to engineering education. Statistical assumptions were tested and confirmed the linearity of the relationship between the IV and DV logit, a lack of significant multicollinearity and lack of influential outliers supporting the use of this procedure. The logistic regression model was not statistically significant, χ2(1) = 0.076, p=0.783.

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	887	96.3
	Missing Cases	34	3.7
	Total	921	100.0
Unselected Cases		0	.0
Total		921	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
No	0
Yes	1

Classification Table[a,b]

			Predicted		
			Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no		Percentage Correct
	Observed		No	Yes	
Step 0	Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no	No	659	0	100.0
		Yes	228	0	.0
	Overall Percentage				74.3

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-1.061	.077	190.826	1	<.001	.346

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	General Cultural Capital Total	.076	1	.783
	Overall Statistics		.076	1	.783

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	.076	1	.783
	Block	.076	1	.783
	Model	.076	1	.783

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1011.006[a]	.000	.000

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	9.196	8	.326

Classification Table[a]

			Predicted		
			Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no		Percentage Correct
	Observed		No	Yes	
Step 1	Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no	No	659	0	100.0
		Yes	228	0	.0
	Overall Percentage				74.3

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	General Cultural Capital Total	-.009	.034	.076	1	.783	.991	.927	1.059
	Constant	-1.030	.138	55.454	1	<.001	.357		

a. Variable(s) entered on step 1: General Cultural Capital Total.

Binary Logistic Regression: Engineering Career Aspiration and Archer-Style Engineering Capital

A binary logistic regression was adopted to determine the effect of Archer-style engineering capital score on the likelihood of aspiring to an engineering career. Statistical assumptions were tested and confirmed the linearity of the relationship between the IV and DV logit, a lack of significant multicollinearity and lack of influential outliers supporting the use of this procedure. The logistic regression model was statistically significant, χ2(1) = 296.034, p<0.001. The model explained 38.8% (Nagelkerke R^2) of the variance in career aspiration and correctly classified 75.8% of cases. Sensitivity was 54.4%, specificity was 87.5%. Increasing Archer-style engineering capital score was associated with a greater likelihood of aspiring to engineering career pathways.

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	892	96.9
	Missing Cases	29	3.1
	Total	921	100.0
Unselected Cases		0	.0
Total		921	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
No	0
Yes	1

Classification Table[a,b]

			Predicted		
			57. Do you think you might like to work in an engineering-related job in the future?		Percentage Correct
	Observed		No	Yes	
Step 0	57. Do you think you might like to work in an engineering-related job in the future?	No	576	0	100.0
		Yes	316	0	.0
	Overall Percentage				64.6

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.600	.070	73.549	1	<.001	.549

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	AS Engineering Capital Total on 0-105 Scale to 0dp	258.235	1	<.001
	Overall Statistics		258.235	1	<.001

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	296.034	1	<.001
	Block	296.034	1	<.001
	Model	296.034	1	<.001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	863.645[a]	.282	.388

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	9.894	8	.273

Classification Table[a]

			Predicted		
			57. Do you think you might like to work in an engineering-related job in the future?		Percentage Correct
	Observed		No	Yes	
Step 1	57. Do you think you might like to work in an engineering-related job in the future?	No	504	72	87.5
		Yes	144	172	54.4
	Overall Percentage				75.8

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	AS Engineering Capital Total on 0-105 Scale to 0dp	.114	.008	184.718	1	<.001	1.121	1.102	1.139
	Constant	-4.686	.319	215.798	1	<.001	.009		

a. Variable(s) entered on step 1: AS Engineering Capital Total on 0-105 Scale to 0dp.

Binary Logistic Regression: Engineering Career Aspiration and Science Capital

A binary logistic regression was adopted to determine the effect of science capital score on the likelihood of aspiring to engineering careers. Statistical assumptions were tested and confirmed the linearity of the relationship between the IV and DV logit, a lack of significant multicollinearity and lack of influential outliers supporting the use of this procedure. The logistic regression model was statistically significant, χ2(1) = 8.990, p=0.003. The model explained 1.4% (Nagelkerke R^2) of the variance in career aspiration and correctly classified 64.9% of cases. Sensitivity was 0.9%, specificity was 100.0%. Increasing science capital score was associated with a greater likelihood of aspiring to engineering career pathways – however, notably this performance was poor for those who aspired to engineering careers.

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	892	96.9
	Missing Cases	29	3.1
	Total	921	100.0
Unselected Cases		0	.0
Total		921	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
No	0
Yes	1

Classification Table[a,b]

			Predicted		
			57. Do you think you might like to work in an engineering-related job in the future?		Percentage Correct
	Observed		No	Yes	
Step 0	57. Do you think you might like to work in an engineering-related job in the future?	No	576	0	100.0
		Yes	316	0	.0
	Overall Percentage				64.6

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.600	.070	73.549	1	<.001	.549

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Science Capital Total on 0-105 Scale	9.005	1	.003
	Overall Statistics		9.005	1	.003

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	8.990	1	.003
	Block	8.990	1	.003
	Model	8.990	1	.003

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1150.689[a]	.010	.014

a. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	7.434	8	.491

Classification Table[a]

			Predicted		
			57. Do you think you might like to work in an engineering-related job in the future?		Percentage Correct
	Observed		No	Yes	
Step 1	57. Do you think you might like to work in an engineering-related job in the future?	No	576	0	100.0
		Yes	313	3	.9
	Overall Percentage				64.9

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Science Capital Total on 0-105 Scale	.015	.005	8.910	1	.003	1.015	1.005	1.025
	Constant	-1.229	.224	30.116	1	<.001	.292		

a. Variable(s) entered on step 1: Science Capital Total on 0-105 Scale.

Binary Logistic Regression: Engineering Career Aspiration and General Cultural Capital

A binary logistic regression was adopted to determine the effect of general cultural capital score on the likelihood of aspiring to engineering education. Statistical assumptions were tested and confirmed the linearity of the relationship between the IV and DV logit, a lack of significant multicollinearity and lack of influential outliers supporting the use of this procedure. The logistic regression model was not statistically significant, χ2(1) = 1.129, p=0.270.

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	892	96.9
	Missing Cases	29	3.1
	Total	921	100.0
Unselected Cases		0	.0
Total		921	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
No	0
Yes	1

Classification Table[a,b]

			Predicted		
			57. Do you think you might like to work in an engineering-related job in the future?		Percentage Correct
	Observed		No	Yes	
Step 0	57. Do you think you might like to work in an engineering-related job in the future?	No	576	0	100.0
		Yes	316	0	.0
	Overall Percentage				64.6

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.600	.070	73.549	1	<.001	.549

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	General Cultural Capital Total	1.219	1	.270
	Overall Statistics		1.219	1	.270

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	1.219	1	.270
	Block	1.219	1	.270
	Model	1.219	1	.270

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1158.459[a]	.001	.002

a. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	6.744	8	.564

Classification Table[a]

			Predicted		
			57. Do you think you might like to work in an engineering-related job in the future?		Percentage Correct
	Observed		No	Yes	
Step 1	57. Do you think you might like to work in an engineering-related job in the future?	No	576	0	100.0
		Yes	316	0	.0
	Overall Percentage				64.6

a. The cut value is .500

Variables in the Equation

								95% C.I.for EXP(B)	
		B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Step 1[a]	General Cultural Capital Total	-.034	.031	1.218	1	.270	.966	.909	1.027
	Constant	-.485	.125	15.042	1	<.001	.616		

a. Variable(s) entered on step 1: General Cultural Capital Total.

Directory of Statistical Analyses Outputs for Chapter Six

Cronbach’s Alpha Analysis: Engineering Literacy Instrument

A Cronbach’s Alpha analysis was utilised to examine the internal consistency (reliability) of responses on the engineering literacy scale. Six items were examined and determined to possess a high level of internal consistency (N=865, a=0.761) supporting the use of this scale. This result was not meaningfully improved by the removal of any of the items.

Case Processing Summary

		N	%
Cases	Valid	865	93.9
	Excluded[a]	56	6.1
	Total	921	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.761	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
39.8. ...Know a lot about engineering"	-.60	13.492	.427	.749
46.3. I have learnt a lot about engineering from museums	-.04	13.545	.444	.743
40.6. I know how to design and make things	-1.03	13.635	.467	.736
40.7. I know quite a lot about engineering	-.13	11.992	.721	.666
52.2. Engineers need to be imaginative in their work	-1.37	15.672	.305	.770
40.8. I would be confident talking about engineering in lessons	-.05	12.003	.670	.678

Principal Components Analysis: Engineering Literacy Instrument

A Principal Components Analysis (PCA) was run on a seven-item instrument measuring the engineering literacy of 855 participants. The suitability of PCA was confirmed with a Kaiser-Meyer-Olkin (KMO) measure of 0.783 and a statistically significant Bartlett's test (p<0.001).

The PCA resolved to two components with an eigenvalue greater than one which explained 55.04% of total variance. Examination of component loadings revealed a single item "Anyone can become an engineer" poorly loaded with the remaining six items. Whilst understanding that anyone can become an engineer might be considered a form of literacy for engineering supporting its theoretical value this item was removed for a further PCA analysis. The second PCA analysis (KMO=0.784, Bartlett's test p<0.001) resolved to a single component that was robustly loaded to by all six items. This supports the dimensionality of the engineering literacy measure.

PCA One:

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
39.8. ...Know a lot about engineering"	-.04	1.146	855
46.3. I have learnt a lot about engineering from museums	-.60	1.111	855
27.8. Anyone can become an engineer	.67	1.131	855
40.6. I know how to design and make things	.39	1.053	855
40.7. I know quite a lot about engineering	-.51	1.059	855
52.2. Engineers need to be imaginative in their work	.73	.839	855
40.8. I would be confident talking about engineering in lessons	-.59	1.112	855

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.783
Bartlett's Test of Sphericity	Approx. Chi-Square	1431.223
	df	21
	Sig.	.000

Communalities

	Initial	Extraction
39.8. ...Know a lot about engineering"	1.000	.398
46.3. I have learnt a lot about engineering from museums	1.000	.394
27.8. Anyone can become an engineer	1.000	.847
40.6. I know how to design and make things	1.000	.419
40.7. I know quite a lot about engineering	1.000	.763
52.2. Engineers need to be imaginative in their work	1.000	.318
40.8. I would be confident talking about engineering in lessons	1.000	.715

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.815	40.217	40.217	2.815	40.217	40.217
2	1.038	14.824	55.040	1.038	14.824	55.040
3	.843	12.045	67.086			
4	.760	10.851	77.936			
5	.707	10.099	88.035			
6	.605	8.645	96.680			
7	.232	3.320	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component	
	1	2
40.7. I know quite a lot about engineering	.862	-.140
40.8. I would be confident talking about engineering in lessons	.838	-.112
40.6. I know how to design and make things	.645	.052
46.3. I have learnt a lot about engineering from museums	.618	.109
39.8. ...Know a lot about engineering"	.605	-.179
52.2. Engineers need to be imaginative in their work	.448	.343
27.8. Anyone can become an engineer	.075	.917

Extraction Method: Principal Component Analysis.

PCA Two:

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
39.8. ...Know a lot about engineering"	-.04	1.146	865
46.3. I have learnt a lot about engineering from museums	-.60	1.109	865
40.6. I know how to design and make things	.38	1.058	865
40.7. I know quite a lot about engineering	-.52	1.060	865
52.2. Engineers need to be imaginative in their work	.73	.839	865
40.8. I would be confident talking about engineering in lessons	-.59	1.112	865

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.784
Bartlett's Test of Sphericity	Approx. Chi-Square	1419.343
	df	15
	Sig.	.000

Communalities

	Initial	Extraction
39.8. ...Know a lot about engineering"	1.000	.363
46.3. I have learnt a lot about engineering from museums	1.000	.378
40.6. I know how to design and make things	1.000	.416
40.7. I know quite a lot about engineering	1.000	.747
52.2. Engineers need to be imaginative in their work	1.000	.198
40.8. I would be confident talking about engineering in lessons	1.000	.698

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.801	46.688	46.688	2.801	46.688	46.688
2	.874	14.571	61.259			
3	.771	12.853	74.112			
4	.714	11.902	86.014			
5	.602	10.039	96.053			
6	.237	3.947	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component
	1
40.7. I know quite a lot about engineering	.864
40.8. I would be confident talking about engineering in lessons	.835
40.6. I know how to design and make things	.645
46.3. I have learnt a lot about engineering from museums	.615
39.8. ...Know a lot about engineering"	.603
52.2. Engineers need to be imaginative in their work	.445

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Cronbach's Alpha Analysis: Engineering Attitudes Instrument

A Cronbach's Alpha analysis was utilised to examine the internal consistency (reliability) of responses on the engineering attitudes scale. Seven items were examined and determined to possess a high level of internal consistency (N=867, a=0.802) supporting the use of this scale. This result was not meaningfully improved by the removal of any of the items.

Case Processing Summary

		N	%
Cases	Valid	867	94.1
	Excluded[a]	54	5.9
	Total	921	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.802	7

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
39.5. ...Think that engineering is very interesting"	1.79	17.851	.566	.771
39.6. ...Think it is important for me to learn about engineering"	2.02	18.124	.548	.774
46.1. My family like going to museums	1.94	18.148	.456	.792
46.2. I like going to museums	2.00	17.561	.460	.795
52.3. Engineering creates new jobs so more people can have work	1.51	19.289	.530	.779
52.4. It is useful to know about engineering in my daily life	1.87	17.449	.639	.757
52.5. Getting young people to understand engineering is important for our society	1.72	18.309	.601	.766

Principal Components Analysis: Engineering Attitudes Instrument

A Principal Components Analysis (PCA) was run on a seven-item instrument measuring the engineering attitudes of 867 participants. The suitability of PCA was confirmed with a Kaiser-Meyer-Olkin (KMO) measure of 0.733 and a statistically significant Bartlett’s test (p<0.001).

The PCA resolved to two components with an eigenvalue greater than one which explained 67.72% of total variance. Examination of component loadings revealed whilst all items loaded well to component one (all items >0.5) component two only loaded well with two items: “My family like going to museums” and “I like going to museums”. These items are consistent with attitudes towards learning contexts in which engineering may take place and are consistent with both uses of Bourdieu and Archer and colleagues. For this reason, it was determined that the strong loadings of all items in component one was sufficient evidence to validate the seven item measure of engineering attitudes. However, further research may wish to consider the deeper relationship between engineering and museum contexts.

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
39.5. ...Think that engineering is very interesting"	.35	1.032	867
39.6. ...Think it is important for me to learn about engineering"	.12	1.010	867
46.1. My family like going to museums	.20	1.136	867
46.2. I like going to museums	.15	1.236	867
52.3. Engineering creates new jobs so more people can have work	.63	.832	867
52.4. It is useful to know about engineering in my daily life	.27	1.009	867
52.5. Getting young people to understand engineering is important for our society	.42	.915	867

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.733
Bartlett's Test of Sphericity	Approx. Chi-Square	2654.670
	df	21
	Sig.	.000

Communalities

	Initial	Extraction
39.5. ...Think that engineering is very interesting"	1.000	.599
39.6. ...Think it is important for me to learn about engineering"	1.000	.607
46.1. My family like going to museums	1.000	.852
46.2. I like going to museums	1.000	.858
52.3. Engineering creates new jobs so more people can have work	1.000	.484
52.4. It is useful to know about engineering in my daily life	1.000	.691
52.5. Getting young people to understand engineering is important for our society	1.000	.649

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.324	47.482	47.482	3.324	47.482	47.482
2	1.417	20.240	67.721	1.417	20.240	67.721
3	.924	13.202	80.923			
4	.510	7.283	88.206			
5	.291	4.152	92.358			
6	.273	3.895	96.252			
7	.262	3.748	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component	
	1	2
52.4. It is useful to know about engineering in my daily life	.806	-.204
52.5. Getting young people to understand engineering is important for our society	.776	-.218
39.5. ...Think that engineering is very interesting"	.728	-.262
39.6. ...Think it is important for me to learn about engineering"	.717	-.306
52.3. Engineering creates new jobs so more people can have work	.691	-.081
46.1. My family like going to museums	.517	.765
46.2. I like going to museums	.533	.758

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

Cronbach's Alpha Analysis: Knowledge of Engineering Pathways Instrument

A Cronbach's Alpha analysis was utilised to examine the internal consistency (reliability) of responses on the knowledge of engineering pathways scale. Five items were examined and determined to possess a high level of internal consistency (N=863, a=0.762) supporting the use of this scale. This result was not meaningfully improved by the removal of any of the items.

Case Processing Summary

		N	%
Cases	Valid	863	93.7
	Excluded[a]	58	6.3
	Total	921	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.762	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
28.2. It is important to understand engineering even if you don't want an engineering job in the future	.37	9.453	.463	.742
28.3. An engineering qualification can help you get many different types of job	.03	9.562	.465	.741
39.7. ...Has explained to me that understanding engineering is useful for my future"	.67	8.449	.528	.721
51.4. My teachers explain how engineering qualifications can lead to different jobs	.79	8.154	.588	.698
51.6. My teachers have explained to me that understanding engineering is useful for my future	1.02	7.952	.615	.687

Principal Components Analysis: Knowledge of Engineering Pathways Instrument

A Principal Components Analysis (PCA) was run on a five-item instrument measuring theknowledge of engineering pathways of 863 participants. The suitability of PCA was confirmed with a Kaiser-Meyer-Olkin (KMO) measure of 0.691 and a statistically significant Bartlett's test (p<0.001).

The PCA resolved to two components with an eigenvalue greater than one which explained 73.08% of total variance. Examination of component loadings revealed whilst all items loaded well to component one (all items >0.6) component two only loaded well with two items: "An engineering qualification can help you get many different types of job" and "It is important to understand engineering even if you don't want an engineering job in the future". These two items relate to the view of the individual compared to the remaining three which relate to the influence of parents and teachers. It is therefore understandable that these two items may be distinguished as a separate component however the strong loading of all five items to the first component highlights the interconnectedness of these items and supports the use of this instrument as a measure of knowledge of engineering pathways. Further research may wish to study distinctions in the influence of others vs. held understandings of engineering pathways to expand understanding of this subcomponent.

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
28.3. An engineering qualification can help you get many different types of job	.69	.876	863
28.2. It is important to understand engineering even if you don't want an engineering job in the future	.35	.906	863
39.7. ...Has explained to me that understanding engineering is useful for my future"	.05	1.065	863
51.4. My teachers explain how engineering qualifications can lead to different jobs	-.07	1.063	863
51.6. My teachers have explained to me that understanding engineering is useful for my future	-.30	1.078	863

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.691
Bartlett's Test of Sphericity	Approx. Chi-Square	1349.746
	df	10
	Sig.	.000

Communalities

	Initial	Extraction
28.3. An engineering qualification can help you get many different types of job	1.000	.700
28.2. It is important to understand engineering even if you don't want an engineering job in the future	1.000	.742
39.7. ...Has explained to me that understanding engineering is useful for my future"	1.000	.516
51.4. My teachers explain how engineering qualifications can lead to different jobs	1.000	.851
51.6. My teachers have explained to me that understanding engineering is useful for my future	1.000	.846

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.565	51.308	51.308	2.565	51.308	51.308
2	1.089	21.770	73.078	1.089	21.770	73.078
3	.617	12.335	85.413			
4	.475	9.506	94.919			
5	.254	5.081	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component	
	1	2
51.6. My teachers have explained to me that understanding engineering is useful for my future	.788	-.475
51.4. My teachers explain how engineering qualifications can lead to different jobs	.767	-.512
39.7. ...Has explained to me that understanding engineering is useful for my future"	.713	.082
28.3. An engineering qualification can help you get many different types of job	.652	.524
28.2. It is important to understand engineering even if you don't want an engineering job in the future	.650	.564

Cronbach's Alpha Analysis: Consumption of Engineering Media Instrument

A Cronbach's Alpha analysis was utilised to examine the internal consistency (reliability) of responses on the consumption of engineering media scale. Four items were examined and determined to possess a high level of internal consistency (N=890, a=0.796) supporting the use of this scale. This result was not meaningfully improved by the removal of any of the items.

Case Processing Summary

		N	%
Cases	Valid	890	96.6
	Excluded[a]	31	3.4
	Total	921	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.796	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.	3.81	7.227	.683	.707
43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.	2.93	8.086	.518	.789
43.4. Read books or magazines about engineering?	4.38	8.493	.651	.737
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	3.90	6.970	.616	.746

Principal Components Analysis: Consumption of Engineering Media Instrument

A Principal Components Analysis (PCA) was run on a four-item instrument measuring the consumption of engineering media of 863 participants. The suitability of PCA was confirmed with a Kaiser-Meyer-Olkin (KMO) measure of 0.779 and a statistically significant Bartlett's test (p<0.001). The PCA resolved to a single component with an eigenvalue greater than one which explained 63.13% of total variance. Examination of component loadings revealed that all items loaded well to component one (>0.7) supporting the dimensionality of this instrument measure.

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.	1.19	1.156	890
43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.	2.08	1.152	890
43.4. Read books or magazines about engineering?	.62	.916	890
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	1.11	1.286	890

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.779
Bartlett's Test of Sphericity	Approx. Chi-Square	1136.714
	df	6
	Sig.	.000

Communalities

	Initial	Extraction
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.	1.000	.709
43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.	1.000	.503
43.4. Read books or magazines about engineering?	1.000	.671
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	1.000	.642

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.525	63.127	63.127	2.525	63.127	63.127
2	.654	16.355	79.482			
3	.430	10.749	90.231			
4	.391	9.769	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix^a

	Component
	1
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.	.842
43.4. Read books or magazines about engineering?	.819
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	.801
43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.	.709

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Cronbach’s Alpha Analysis: Engineering Out-Of-School Learning Contexts Instrument

A Cronbach’s Alpha analysis was utilised to examine the internal consistency (reliability) of responses on the engineering out-of-school learning contexts scale. Fifteen items were examined and determined to possess a high level of internal consistency (N=852, a=0.810 based on standardised items) supporting the use of this scale. This result was not meaningfully improved by the removal of any of the items.

Case Processing Summary

		N	%
Cases	Valid	852	92.5
	Excluded[a]	69	7.5
	Total	921	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.800	.810	15

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
39.1. ...Sign me up to activities outside of school time (e.g. dance, music, clubs)"	19.94	71.988	.193	.124	.805
44.1. Go to a museum?	19.15	69.646	.455	.572	.786
44.2. Go to a science centre, science museum, or planetarium?	19.42	69.088	.509	.592	.783
44.4. Do DIY, or help fix things around the home?	18.13	64.947	.490	.432	.781
44.5. Get shown how to use tools?	18.26	64.869	.489	.412	.782
44.6. Make models, e.g. playing with Lego, painting miniatures?	18.39	62.958	.555	.412	.775

44.7. Do crafts, e.g. knitting, woodwork?	18.63	63.583	.505	.377	.780
44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?	17.57	68.896	.277	.190	.801
44.9. Program computers, e.g. writing apps, building websites?	19.32	67.196	.361	.188	.793
45.2. Go to an after school club that involves engineering?	20.26	72.419	.359	.275	.793
45.3. Had people visit you in school to teach you about engineering?	19.86	70.799	.393	.321	.790
45.4. Take an engineering related school trip?	20.13	72.050	.385	.407	.792
45.6. Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes	18.96	66.163	.469	.274	.783
45.7. Take part in a competition where you design or make something?	19.60	66.952	.523	.334	.780
45.5. Take a school trip to a museum?	19.71	72.862	.299	.241	.796

Principal Components Analysis: Engineering Out-of-School Learning Contexts Instrument

A Principal Components Analysis (PCA) was run on a fifteen-item instrument measuring the engineering out-of-school learning contexts of 852 participants. The suitability of PCA was confirmed with a Kaiser-Meyer-Olkin (KMO) measure of 0.812 and a statistically significant Bartlett's test (p<0.001). No rotation was applied.

The PCA resolved to four components with an eigenvalue greater than one which explained 57.47% of total variance. It is unsurprising that four components emerged from this analysis given the variety of contexts included within this theoretical subcomponent. Examination of component loadings revealed inconsistent loadings. The first component was loaded to by all items to some degree (>0.3), the second loaded by items related to school contexts, the third with home contexts and finally the fourth with museum trips or the use of computers. Loadings between these four components was not entirely clear necessitating further examination. To clarify this structure a second PCA was adopted to examine this same data but with a Direct Oblimin rotation – this approach would allow components to correlate but distinguish loadings to ease interpretation of components.

The second PCA was also found to be valid with a Kaiser-Meyer-Olkin (KMO) measure of 0.812 and a statistically significant Bartlett's test (p<0.001). The PCA resolved to four components with an eigenvalue greater than one which explained 57.47% of total variance. The Direct Oblimin rotation eased interpretation of component contents. The first component now related specifically to designing and making things with four items: "Do DIY, or help fix things around the home?", "Get shown how to use tools?", "Do crafts, e.g. knitting, woodwork?", and "Make models, e.g. playing with Lego painting miniatures?". The second component related to school experiences with items such as "Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes", "Take part in a competition where you design or make something", "Take a school trip to a museum", "Take an engineering related school trip", "Had people visit you in school to teach you about engineering?", and "Go to an after school club that involves engineering". The third component related to family contexts with items such as "…Go to a science centre, science museum, or planetarium?", "…Sign me up to activities outside school time (e.g. dance, music, clubs)", and "Go to a museum?" . The fourth component was no longer concerned with museum visits but only included items related to recreational making: "Play videogames about designing or building, e.g. The Sims, Minecraft", "Program computers, e.g. writing apps, building websites", "Make models e.g. playing with Lego, painting miniatures".

Whilst not a simplistic structure these components align with the theoretical underpinning of the Out-of-School Learning Contexts subcomponent as a diverse conceptualisation of how engineering capital may be sourced by young learners.

PCA One:

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
39.1. ...Sign me up to activities outside of school time (e.g. dance, music, clubs)"	.58	1.189	852
44.1. Go to a museum?	1.37	.900	852
44.2. Go to a science centre, science museum, or planetarium?	1.10	.878	852
44.4. Do DIY, or help fix things around the home?	2.39	1.337	852
44.5. Get shown how to use tools?	2.26	1.346	852
44.6. Make models, e.g. playing with Lego, painting miniatures?	2.13	1.405	852
44.7. Do crafts, e.g. knitting, woodwork?	1.90	1.444	852
44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?	2.95	1.401	852
44.9. Program computers, e.g. writing apps, building websites?	1.21	1.383	852
45.2. Go to an after school club that involves engineering?	.27	.715	852
45.3. Had people visit you in school to teach you about engineering?	.66	.869	852
45.4. Take an engineering related school trip?	.40	.722	852
45.5. Take a school trip to a museum?	.82	.756	852
45.6. Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes	1.56	1.252	852
45.7. Take part in a competition where you design or make something?	.92	1.073	852

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.812
Bartlett's Test of Sphericity	Approx. Chi-Square	3463.135
	df	105
	Sig.	.000

Communalities

	Initial	Extraction
39.1. ...Sign me up to activities outside of school time (e.g. dance, music, clubs)"	1.000	.434
44.1. Go to a museum?	1.000	.829
44.2. Go to a science centre, science museum, or planetarium?	1.000	.810
44.4. Do DIY, or help fix things around the home?	1.000	.672
44.5. Get shown how to use tools?	1.000	.625
44.6. Make models, e.g. playing with Lego, painting miniatures?	1.000	.605
44.7. Do crafts, e.g. knitting, woodwork?	1.000	.570
44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?	1.000	.600
44.9. Program computers, e.g. writing apps, building websites?	1.000	.495
45.2. Go to an after school club that involves engineering?	1.000	.475
45.3. Had people visit you in school to teach you about engineering?	1.000	.527
45.4. Take an engineering related school trip?	1.000	.657
45.5. Take a school trip to a museum?	1.000	.456
45.6. Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes	1.000	.401
45.7. Take part in a competition where you design or make something?	1.000	.464

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.230	28.197	28.197	4.230	28.197	28.197
2	1.806	12.039	40.236	1.806	12.039	40.236
3	1.424	9.495	49.732	1.424	9.495	49.732
4	1.160	7.736	57.467	1.160	7.736	57.467
5	.897	5.981	63.448			
6	.776	5.171	68.619			
7	.737	4.916	73.535			
8	.704	4.693	78.228			
9	.620	4.130	82.358			
10	.582	3.883	86.242			
11	.554	3.693	89.934			
12	.461	3.074	93.008			
13	.419	2.793	95.801			
14	.384	2.562	98.363			
15	.246	1.637	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component			
	1	2	3	4
45.7. Take part in a competition where you design or make something?	.637	.143	-.139	-.137
44.2. Go to a science centre, science museum, or planetarium?	.636	.017	.530	.352
44.6. Make models, e.g. playing with Lego, painting miniatures?	.621	-.406	-.165	.163
44.7. Do crafts, e.g. knitting, woodwork?	.586	-.449	-.046	-.151
45.6. Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes	.572	.068	-.239	-.111
44.5. Get shown how to use tools?	.568	-.433	-.067	-.332
44.4. Do DIY, or help fix things around the home?	.567	-.462	-.076	-.362
45.3. Had people visit you in school to teach you about engineering?	.528	.454	-.158	-.131
45.2. Go to an after school club that involves engineering?	.490	.474	-.099	.004
44.9. Program computers, e.g. writing apps, building websites?	.447	-.056	-.320	.436
45.4. Take an engineering related school trip?	.531	.586	-.089	-.155
45.5. Take a school trip to a museum?	.430	.470	.154	-.163
44.1. Go to a museum?	.578	-.054	.605	.355
39.1. ...Sign me up to activities outside of school time (e.g. dance, music, clubs)"	.281	-.077	.553	-.207
44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?	.348	-.072	-.432	.536

Extraction Method: Principal Component Analysis.

a. 4 components extracted.

PCA Two:

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
39.1. ...Sign me up to activities outside of school time (e.g. dance, music, clubs)"	.58	1.189	852
44.1. Go to a museum?	1.37	.900	852
44.2. Go to a science centre, science museum, or planetarium?	1.10	.878	852
44.4. Do DIY, or help fix things around the home?	2.39	1.337	852
44.5. Get shown how to use tools?	2.26	1.346	852
44.6. Make models, e.g. playing with Lego, painting miniatures?	2.13	1.405	852
44.7. Do crafts, e.g. knitting, woodwork?	1.90	1.444	852
44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?	2.95	1.401	852
44.9. Program computers, e.g. writing apps, building websites?	1.21	1.383	852
45.2. Go to an after school club that involves engineering?	.27	.715	852
45.3. Had people visit you in school to teach you about engineering?	.66	.869	852
45.4. Take an engineering related school trip?	.40	.722	852
45.5. Take a school trip to a museum?	.82	.756	852
45.6. Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes	1.56	1.252	852
45.7. Take part in a competition where you design or make something?	.92	1.073	852

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.812
Bartlett's Test of Sphericity	Approx. Chi-Square	3463.135
	df	105
	Sig.	.000

Communalities

	Initial	Extraction
39.1. ...Sign me up to activities outside of school time (e.g. dance, music, clubs)"	1.000	.434
44.1. Go to a museum?	1.000	.829
44.2. Go to a science centre, science museum, or planetarium?	1.000	.810
44.4. Do DIY, or help fix things around the home?	1.000	.672
44.5. Get shown how to use tools?	1.000	.625
44.6. Make models, e.g. playing with Lego, painting miniatures?	1.000	.605
44.7. Do crafts, e.g. knitting, woodwork?	1.000	.570
44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?	1.000	.600
44.9. Program computers, e.g. writing apps, building websites?	1.000	.495
45.2. Go to an after school club that involves engineering?	1.000	.475
45.3. Had people visit you in school to teach you about engineering?	1.000	.527
45.4. Take an engineering related school trip?	1.000	.657
45.5. Take a school trip to a museum?	1.000	.456
45.6. Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes	1.000	.401
45.7. Take part in a competition where you design or make something?	1.000	.464

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	4.230	28.197	28.197	4.230	28.197	28.197	3.047
2	1.806	12.039	40.236	1.806	12.039	40.236	3.037
3	1.424	9.495	49.732	1.424	9.495	49.732	2.456
4	1.160	7.736	57.467	1.160	7.736	57.467	1.791
5	.897	5.981	63.448				
6	.776	5.171	68.619				
7	.737	4.916	73.535				
8	.704	4.693	78.228				
9	.620	4.130	82.358				
10	.582	3.883	86.242				
11	.554	3.693	89.934				
12	.461	3.074	93.008				
13	.419	2.793	95.801				
14	.384	2.562	98.363				
15	.246	1.637	100.000				

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Component Matrix[a]

	Component			
	1	2	3	4
45.7. Take part in a competition where you design or make something?	.637	.143	-.139	-.137
44.2. Go to a science centre, science museum, or planetarium?	.636	.017	.530	.352
44.6. Make models, e.g. playing with Lego, painting miniatures?	.621	-.406	-.165	.163
44.7. Do crafts, e.g. knitting, woodwork?	.586	-.449	-.046	-.151
45.6. Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes	.572	.068	-.239	-.111
44.5. Get shown how to use tools?	.568	-.433	-.067	-.332
44.4. Do DIY, or help fix things around the home?	.567	-.462	-.076	-.362
45.3. Had people visit you in school to teach you about engineering?	.528	.454	-.158	-.131
45.2. Go to an after school club that involves engineering?	.490	.474	-.099	.004
44.9. Program computers, e.g. writing apps, building websites?	.447	-.056	-.320	.436
45.4. Take an engineering related school trip?	.531	.586	-.089	-.155
45.5. Take a school trip to a museum?	.430	.470	.154	-.163
44.1. Go to a museum?	.578	-.054	.605	.355
39.1. …Sign me up to activities outside of school time (e.g. dance, music, clubs)”	.281	-.077	.553	-.207
44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?	.348	-.072	-.432	.536

Extraction Method: Principal Component Analysis.

a. 4 components extracted.

Pattern Matrix[a]

	Component			
	1	2	3	4
44.4. Do DIY, or help fix things around the home?	.843	.007	-.042	-.085
44.5. Get shown how to use tools?	.802	.022	-.020	-.068
44.7. Do crafts, e.g. knitting, woodwork?	.709	-.048	.103	.079
44.6. Make models, e.g. playing with Lego, painting miniatures?	.532	-.074	.181	.411
45.4. Take an engineering related school trip?	-.059	.832	-.020	-.030
45.3. Had people visit you in school to teach you about engineering?	.036	.721	-.058	.042
45.2. Go to an after school club that involves engineering?	-.090	.664	.051	.112
45.5. Take a school trip to a museum?	-.070	.637	.159	-.179
45.7. Take part in a competition where you design or make something?	.315	.503	.011	.086
45.6. Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes	.343	.418	-.078	.156
44.1. Go to a museum?	-.023	-.006	.911	.100
44.2. Go to a science centre, science museum, or planetarium?	-.029	.099	.859	.143
39.1. ...Sign me up to activities outside of school time (e.g. dance, music, clubs)"	.198	.028	.463	-.407
44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?	-.010	.013	.041	.771
44.9. Program computers, e.g. writing apps, building websites?	.063	.086	.114	.646

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.[a]

a. Rotation converged in 8 iterations.

Structure Matrix

	Component			
	1	2	3	4
44.4. Do DIY, or help fix things around the home?	.815	.177	.209	.085
44.5. Get shown how to use tools?	.788	.191	.223	.098
44.7. Do crafts, e.g. knitting, woodwork?	.745	.158	.305	.217
44.6. Make models, e.g. playing with Lego, painting miniatures?	.652	.170	.334	.512
45.4. Take an engineering related school trip?	.122	.807	.179	.105
45.3. Had people visit you in school to teach you about engineering?	.195	.722	.143	.175
45.2. Go to an after school club that involves engineering?	.103	.677	.202	.214
45.5. Take a school trip to a museum?	.089	.631	.298	-.075
45.7. Take part in a competition where you design or make something?	.452	.594	.240	.239
45.6. Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes	.449	.505	.139	.297
44.1. Go to a museum?	.267	.245	.905	.125
44.2. Go to a science centre, science museum, or planetarium?	.279	.343	.881	.184
39.1. ...Sign me up to activities outside of school time (e.g. dance, music, clubs)"	.260	.123	.515	-.346
44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?	.162	.158	.068	.773
44.9. Program computers, e.g. writing apps, building websites?	.248	.245	.178	.678

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

Principal Components Analysis: All Engineering Capital Subcomponent Instrument Items

A Principal Components Analysis (PCA) was run on 47 items drawn from the engineering capital subcomponent and engineering DV measures. Data from 733 participants was included in this analysis. The use of a PCA was deemed appropriate with a recorded Kaiser-Meyer-Olkin (KMO) measure of 0.928 and a statistically significant Bartlett's test ($p<0.001$). A Direct Oblimin rotation was applied to ease interpretation of resulting components.

The PCA resolved to ten components with an eigenvalue greater than one which explained 63.112% of total variance. Examination of item loadings facilitated an understanding of what each component represented within this output – only items loaded above a 0.4 level were included in components. These components are outlined in the table below.

Component Number	Component Title	Variance Explained	Number of Items	Items
1	Engineering Career Aspiration	28.148%	6	- I would like to have a job that uses engineering - I would like to work in an engineering related job, but not in an engineering industry - I would like to have a job that involves designing and making things - People who are like me work in engineering - I want to become an engineer - Other people think of me as an engineering-type person
2	Museum Visits	7.578%	5	- My family like going to museums - I like going to museums - Go to a museum? - Go to a science centre, science museum, or planetarium? - I have learnt a lot about engineering from museums
3	Engineering Utility	5.225%	4	- Engineers need to be imaginative in their work - Engineering creates new jobs so more people can have work - Getting young people to understand engineering is important for our society - It is useful to know about engineering in my daily life

4	Engineering Curricular-Mapped Experiences	4.369%	5	- Take an engineering related school trip? - Had people visit you in school to teach you about engineering? - Go to an after school club that involves engineering? - Take a school trip to a museum? - Take part in a competition where you design or make something?
5	Making and Fixing	3.828%	4	- Do DIY, or help fix things around the home? - Get shown how to use tools? - Do crafts, e.g. knitting, woodwork? - Make models, e.g. playing with Lego, painting miniatures?
6	Parental Engineering Attitudes	3.531%	4	- ...Know a lot about engineering" - ...Think that engineering is very interesting" - ...Think it is important for me to learn about engineering" - ...Has explained to me that understanding engineering is useful for my future"
7	Teacher Support for Engineering	3.036%	3	- My teachers have explained to me that understanding engineering is useful for my future - My teachers have specifically encouraged me to consider studying engineering after GCSEs - My teachers explain how engineering qualifications can lead to different jobs
8	Engineering Media Consumption	2.710%	4	- Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc. - Read books or magazines about engineering? - Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.

				- Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?
9	Designing and Making with Technology	2.484%	2	- Play videogames about designing or building, e.g. The Sims, Minecraft? - Program computers, e.g. writing apps, building websites?
10	Wider Utility of Engineering	2.204%	2	- An engineering qualification can help you get many different types of job - It is important to understand engineering even if you don't want an engineering job in the future

PCA One:

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
39.8. ...Know a lot about engineering"	-.05	1.145	773
46.3. I have learnt a lot about engineering from museums	-.60	1.105	773
40.6. I know how to design and make things	.38	1.049	773
40.7. I know quite a lot about engineering	-.53	1.052	773
40.8. I would be confident talking about engineering in lessons	-.61	1.110	773
52.2. Engineers need to be imaginative in their work	.73	.837	773
39.5. ...Think that engineering is very interesting"	.34	1.041	773
39.6. ...Think it is important for me to learn about engineering"	.12	1.004	773
46.1. My family like going to museums	.23	1.128	773
46.2. I like going to museums	.16	1.230	773
52.3. Engineering creates new jobs so more people can have work	.64	.834	773
52.4. It is useful to know about engineering in my daily life	.29	1.009	773
52.5. Getting young people to understand engineering is important for our society	.44	.918	773
28.2. It is important to understand engineering even if you don't want an engineering job in the future	.35	.905	773
28.3. An engineering qualification can help you get many different types of job	.68	.880	773
39.7. ...Has explained to me that understanding engineering is useful for my future"	.03	1.065	773
51.4. My teachers explain how engineering qualifications can lead to different jobs	-.08	1.072	773
51.6. My teachers have explained to me that understanding engineering is useful for my future	-.31	1.085	773
AS Eng Cap Talk with Engineering	.611	.6634	773
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.	1.19	1.150	773
43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.	2.06	1.141	773
43.4. Read books or magazines about engineering?	.63	.912	773
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	1.10	1.273	773
39.1. ...Sign me up to activities outside of school time (e.g. dance, music, clubs)"	.60	1.174	773
44.1. Go to a museum?	1.39	.904	773
44.2. Go to a science centre, science museum, or planetarium?	1.10	.878	773

44.4. Do DIY, or help fix things around the home?	2.38	1.334	773
44.5. Get shown how to use tools?	2.26	1.348	773
44.6. Make models, e.g. playing with Lego, painting miniatures?	2.13	1.395	773
44.7. Do crafts, e.g. knitting, woodwork?	1.89	1.447	773
44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?	2.97	1.389	773
44.9. Program computers, e.g. writing apps, building websites?	1.22	1.387	773
45.2. Go to an after school club that involves engineering?	.26	.705	773
45.3. Had people visit you in school to teach you about engineering?	.66	.864	773
45.4. Take an engineering related school trip?	.39	.698	773
45.5. Take a school trip to a museum?	.81	.737	773
45.6. Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes	1.56	1.250	773
45.7. Take part in a competition where you design or make something?	.91	1.055	773
27.5. I would like to have a job that uses engineering	-.32	1.180	773
27.7. I want to become an engineer	-.75	1.086	773
27.6. People who are like me work in engineering	-.43	.997	773
40.5. Other people think of me as an engineering-type person	-.71	1.041	773
51.5. My teachers have specifically encouraged me to consider studying engineering after GCSEs	-.66	.973	773
51.7. I don't think I am clever enough to study any engineering after GCSE	.14	1.184	773
31. When you are not in school how often do you talk about engineering with other people?	1.10	1.292	773
27.9. I would like to have a job that involves designing and making things	.13	1.157	773
27.10. I would like to work in an engineering related job, but not in an engineering industry	-.36	1.001	773

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.928
Bartlett's Test of Sphericity	Approx. Chi-Square	19134.532
	df	1081
	Sig.	.000

Communalities

	Initial	Extraction
39.8. ...Know a lot about engineering"	1.000	.633
46.3. I have learnt a lot about engineering from museums	1.000	.624
40.6. I know how to design and make things	1.000	.594
40.7. I know quite a lot about engineering	1.000	.708
40.8. I would be confident talking about engineering in lessons	1.000	.652
52.2. Engineers need to be imaginative in their work	1.000	.741
39.5. ...Think that engineering is very interesting"	1.000	.753
39.6. ...Think it is important for me to learn about engineering"	1.000	.776
46.1. My family like going to museums	1.000	.730
46.2. I like going to museums	1.000	.707
52.3. Engineering creates new jobs so more people can have work	1.000	.743
52.4. It is useful to know about engineering in my daily life	1.000	.659
52.5. Getting young people to understand engineering is important for our society	1.000	.685
28.2. It is important to understand engineering even if you don't want an engineering job in the future	1.000	.629
28.3. An engineering qualification can help you get many different types of job	1.000	.675
39.7. ...Has explained to me that understanding engineering is useful for my future"	1.000	.752
51.4. My teachers explain how engineering qualifications can lead to different jobs	1.000	.771
51.6. My teachers have explained to me that understanding engineering is useful for my future	1.000	.834
AS Eng Cap Talk with Engineering	1.000	.488
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.	1.000	.665
43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.	1.000	.495
43.4. Read books or magazines about engineering?	1.000	.630
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	1.000	.624
39.1. ...Sign me up to activities outside of school time (e.g. dance, music, clubs)"	1.000	.378
44.1. Go to a museum?	1.000	.701
44.2. Go to a science centre, science museum, or planetarium?	1.000	.674
44.4. Do DIY, or help fix things around the home?	1.000	.669
44.5. Get shown how to use tools?	1.000	.685
44.6. Make models, e.g. playing with Lego, painting miniatures?	1.000	.598
44.7. Do crafts, e.g. knitting, woodwork?	1.000	.612
44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?	1.000	.605
44.9. Program computers, e.g. writing apps, building websites?	1.000	.424
45.2. Go to an after school club that involves engineering?	1.000	.522

45.3. Had people visit you in school to teach you about engineering?	1.000	.516
45.4. Take an engineering related school trip?	1.000	.628
45.5. Take a school trip to a museum?	1.000	.420
45.6. Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes	1.000	.476
45.7. Take part in a competition where you design or make something?	1.000	.538
27.5. I would like to have a job that uses engineering	1.000	.796
27.7. I want to become an engineer	1.000	.733
27.6. People who are like me work in engineering	1.000	.628
40.5. Other people think of me as an engineering-type person	1.000	.704
51.5. My teachers have specifically encouraged me to consider studying engineering after GCSEs	1.000	.759
51.7. I don't think I am clever enough to study any engineering after GCSE	1.000	.225
31. When you are not in school how often do you talk about engineering with other people?	1.000	.588
27.9. I would like to have a job that involves designing and making things	1.000	.638
27.10. I would like to work in an engineering related job, but not in an engineering industry	1.000	.580

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	13.230	28.148	28.148	13.230	28.148	28.148	7.577
2	3.561	7.578	35.726	3.561	7.578	35.726	5.122
3	2.456	5.225	40.950	2.456	5.225	40.950	5.577
4	2.054	4.369	45.320	2.054	4.369	45.320	4.103
5	1.799	3.828	49.147	1.799	3.828	49.147	4.729
6	1.660	3.531	52.678	1.660	3.531	52.678	6.961
7	1.427	3.036	55.715	1.427	3.036	55.715	6.312
8	1.274	2.710	58.424	1.274	2.710	58.424	3.569
9	1.168	2.484	60.909	1.168	2.484	60.909	2.946
10	1.036	2.204	63.112	1.036	2.204	63.112	2.379
11	.980	2.085	65.197				
12	.913	1.942	67.140				
13	.907	1.929	69.068				
14	.840	1.787	70.856				
15	.790	1.682	72.538				
16	.767	1.632	74.170				
17	.706	1.503	75.673				
18	.680	1.446	77.119				
19	.626	1.331	78.450				
20	.613	1.303	79.753				
21	.575	1.224	80.978				
22	.554	1.178	82.156				
23	.551	1.172	83.328				
24	.532	1.132	84.459				
25	.498	1.060	85.519				
26	.473	1.007	86.526				
27	.451	.960	87.486				
28	.433	.921	88.406				
29	.418	.889	89.295				
30	.407	.866	90.161				
31	.395	.840	91.000				
32	.387	.824	91.825				
33	.366	.779	92.604				

34	.339	.720	93.324				
35	.327	.696	94.020				
36	.319	.680	94.700				
37	.314	.667	95.367				
38	.286	.609	95.977				
39	.281	.598	96.574				
40	.248	.529	97.103				
41	.246	.524	97.627				
42	.232	.493	98.120				
43	.204	.434	98.554				
44	.200	.425	98.979				
45	.186	.397	99.376				
46	.151	.322	99.697				
47	.142	.303	100.000				

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Component Matrix^{a}

	Component									
	1	2	3	4	5	6	7	8	9	10
40.7. I know quite a lot about engineering	.784									
40.8. I would be confident talking about engineering in lessons	.744									
40.5. Other people think of me as an engineering-type person	.735									
27.5. I would like to have a job that uses engineering	.704									
31. When you are not in school how often do you talk about engineering with other people?	.693									
52.4. It is useful to know about engineering in my daily life	.673									
39.6. ...Think it is important for me to learn about engineering"	.668									
39.7. ...Has explained to me that understanding engineering is useful for my future"	.667									
39.5. ...Think that engineering is very interesting"	.667									
27.7. I want to become an engineer	.657	-.443								

46.3. I have learnt a lot about engineering from museums	.652								
AS Eng Cap Talk with Engineering	.651								
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	.623								
43.4. Read books or magazines about engineering?	.620								
27.6. People who are like me work in engineering	.615								
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.	.608								
51.6. My teachers have explained to me that understanding engineering is useful for my future	.595			.525					
52.5. Getting young people to understand engineering is important for our society	.580								

27.10. I would like to work in an engineering related job, but not in an engineering industry	.564									
51.5. My teachers have specifically encouraged me to consider studying engineering after GCSEs	.556		.461							
51.4. My teachers explain how engineering qualifications can lead to different jobs	.543		.492							
40.6. I know how to design and make things	.518									
44.5. Get shown how to use tools?	.516									
44.6. Make models, e.g. playing with Lego, painting miniatures?	.503									
39.8. ...Know a lot about engineering"	.493				-.462					
52.3. Engineering creates new jobs so more people can have work	.477	.435								
43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.	.457									

27.9. I would like to have a job that involves designing and making things	.429						-.404			
45.6. Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes	.423									
52.2. Engineers need to be imaginative in their work	.411									
45.2. Go to an after school club that involves engineering?	.400									
44.9. Program computers, e.g. writing apps, building websites?										
51.7. I don't think I am clever enough to study any engineering after GCSE										
44.2. Go to a science centre, science museum, or planetarium?	.433	.578								
44.1. Go to a museum?		.573								
46.1. My family like going to museums		.482	.418							
46.2. I like going to museums		.476								
45.7. Take part in a competition where you design or make something?		.446								

45.5. Take a school trip to a museum?		.404								
45.4. Take an engineering related school trip?				.494						
45.3. Had people visit you in school to teach you about engineering?				.432						
44.4. Do DIY, or help fix things around the home?	.444				.470					
44.7. Do crafts, e.g. knitting, woodwork?	.417				.443					
39.1. ...Sign me up to activities outside of school time (e.g. dance, music, clubs)"										
44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?									.497	
28.3. An engineering qualification can help you get many different types of job	.470									.500
28.2. It is important to understand engineering even if you don't want an engineering job in the future	.475									.487

Extraction Method: Principal Component Analysis.

a. 10 components extracted.

Pattern Matrix[a]

	Component									
	1	2	3	4	5	6	7	8	9	10
27.5. I would like to have a job that uses engineering	.758									
27.10. I would like to work in an engineering related job, but not in an engineering industry	.739									
27.9. I would like to have a job that involves designing and making things	.700									
27.6. People who are like me work in engineering	.695									
27.7. I want to become an engineer	.692									
40.5. Other people think of me as an engineering-type person	.479									
40.8. I would be confident talking about engineering in lessons										
40.7. I know quite a lot about engineering										
40.6. I know how to design and make things										
AS Eng Cap Talk with Engineering										
31. When you are not in school how often do you talk about engineering with other people?										
51.7. I don't think I am clever enough to study any engineering after GCSE										
46.2. I like going to museums		.829								
44.1. Go to a museum?		.804								

44.2. Go to a science centre, science museum, or planetarium?		.733								
46.1. My family like going to museums		.866								
46.3. I have learnt a lot about engineering from museums		.557								
39.1. ...Sign me up to activities outside of school time (e.g. dance, music, clubs)"										
52.2. Engineers need to be imaginative in their work			.907							
52.3. Engineering creates new jobs so more people can have work			.850							
52.5. Getting young people to understand engineering is important for our society			.664							
52.4. It is useful to know about engineering in my daily life			.534							
45.4. Take an engineering related school trip?				.777						
45.3. Had people visit you in school to teach you about engineering?				.659						
45.2. Go to an after school club that involves engineering?				.609						
45.5. Take a school trip to a museum?				.589						
45.7. Take part in a competition where you design or make something?				.517						

45.6. Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes										
44.4. Do DIY, or help fix things around the home?					.812					
44.5. Get shown how to use tools?					.746					
44.7. Do crafts, e.g. knitting, woodwork?					.675					
44.6. Make models, e.g. playing with Lego, painting miniatures?					.464					
39.8. ...Know a lot about engineering"						-.819				
39.5. ...Think that engineering is very interesting"						-.766				
39.6. ...Think it is important for me to learn about engineering"						-.757				
39.7. ...Has explained to me that understanding engineering is useful for my future"						-.742				
51.6. My teachers have explained to me that understanding engineering is useful for my future							-.887			
51.5. My teachers have specifically encouraged me to consider studying engineering after GCSEs							-.862			
51.4. My teachers explain how engineering qualifications can lead to different jobs							-.858			

43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.								-.587		
43.4. Read books or magazines about engineering?								-.554		
43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.								-.525		
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?								-.488		
44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?									.792	
44.9. Program computers, e.g. writing apps, building websites?									.571	
28.3. An engineering qualification can help you get many different types of job										.708
28.2. It is important to understand engineering even if you don't want an engineering job in the future										.677

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.[a]
a. Rotation converged in 22 iterations.

Structure Matrix

	Component									
	1	2	3	4	5	6	7	8	9	10
27.5. I would like to have a job that uses engineering	.861					-.446				
27.7. I want to become an engineer	.810					-.471				
27.6. People who are like me work in engineering	.754									
27.10. I would like to work in an engineering related job, but not in an engineering industry	.743									
40.5. Other people think of me as an engineering-type person	.710					-.572	-.464	-.440		
40.7. I know quite a lot about engineering	.658					-.613	-.508	-.417		
27.9. I would like to have a job that involves designing and making things	.654									
40.8. I would be confident talking about engineering in lessons	.651					-.600	-.439	-.407		
31. When you are not in school how often do you talk about engineering with other people?	.549					-.485		-.464		
AS Eng Cap Talk with Engineering	.521									
40.6. I know how to design and make things	.474				.447					
46.1. My family like going to museums		.844								

44.1. Go to a museum?		.826								
46.2. I like going to museums		.814								
44.2. Go to a science centre, science museum, or planetarium?		.788								
46.3. I have learnt a lot about engineering from museums		.664					-.467			
39.1. ...Sign me up to activities outside of school time (e.g. dance, music, clubs)"										
52.3. Engineering creates new jobs so more people can have work			.853							
52.2. Engineers need to be imaginative in their work			.837							
52.5. Getting young people to understand engineering is important for our society			.774							.401
52.4. It is useful to know about engineering in my daily life			.717			-.462	-.451			
45.4. Take an engineering related school trip?				.784						
45.3. Had people visit you in school to teach you about engineering?				.690						
45.2. Go to an after school club that involves engineering?				.643						

45.5. Take a school trip to a museum?				.601						
45.7. Take part in a competition where you design or make something?				.586	.459					
45.6. Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes				.477						
44.4. Do DIY, or help fix things around the home?					.803					
44.5. Get shown how to use tools?					.752					
44.7. Do crafts, e.g. knitting, woodwork?					.741					
44.6. Make models, e.g. playing with Lego, painting miniatures?					.604				.537	
39.6. ...Think it is important for me to learn about engineering"	.420					-.842				
39.5. ...Think that engineering is very interesting"	.401		.422			-.840				
39.7. ...Has explained to me that understanding engineering is useful for my future"	.403					-.832	-.403			
39.8. ...Know a lot about engineering"						-.784				

51.7. I don't think I am clever enough to study any engineering after GCSE										
51.6. My teachers have explained to me that understanding engineering is useful for my future							-.906			
51.4. My teachers explain how engineering qualifications can lead to different jobs							-.869			
51.5. My teachers have specifically encouraged me to consider studying engineering after GCSEs							-.854			
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.								-.664		
43.4. Read books or magazines about engineering?	.422							-.658		
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	.474							-.610	.442	

43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.					.407			-.552		
44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?									.765	
44.9. Program computers, e.g. writing apps, building websites?									.609	
28.3. An engineering qualification can help you get many different types of job										.741
28.2. It is important to understand engineering even if you don't want an engineering job in the future										.718

Extraction Method: Principal Component Analysis. Rotation Method: Oblimin with Kaiser Normalization.

Component Correlation Matrix

Component	1	2	3	4	5	6	7	8	9	10
1	1.000	.140	.274	.100	.193	-.388	-.317	-.259	.186	.121
2	.140	1.000	.219	.264	.276	-.207	-.185	-.088	.125	.036
3	.274	.219	1.000	.127	.193	-.305	-.330	-.082	.181	.210
4	.100	.264	.127	1.000	.205	-.165	-.270	-.140	.122	-.010
5	.193	.276	.193	.205	1.000	-.226	-.231	-.075	.196	-.040
6	-.388	-.207	-.305	-.165	-.226	1.000	.297	.190	-.013	-.205
7	-.317	-.185	-.330	-.270	-.231	.297	1.000	.120	-.216	-.142
8	-.259	-.088	-.082	-.140	-.075	.190	.120	1.000	-.102	-.115
9	.186	.125	.181	.122	.196	-.013	-.216	-.102	1.000	-.049
10	.121	.036	.210	-.010	-.040	-.205	-.142	-.115	-.049	1.000

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

A second PCA was next necessary to remove items that did not sufficiently load to the ten identified components. Eight items were removed and the PCA analysis was completed again. This second PCA was also found to be valid with a Kaiser-Meyer-Olkin (KMO) measure of 0.913 and a statistically significant Bartlett's test ($p<0.001$). This analysis resolved the same ten components as generated in the first PCA, though some component loadings did change in response to removal of eight items.

PCA Two:

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
39.8. ...Know a lot about engineering"	-.05	1.145	779
46.3. I have learnt a lot about engineering from museums	-.61	1.108	779
52.2. Engineers need to be imaginative in their work	.73	.835	779
39.5. ...Think that engineering is very interesting"	.35	1.039	779
39.6. ...Think it is important for me to learn about engineering"	.12	1.003	779
46.1. My family like going to museums	.22	1.128	779
46.2. I like going to museums	.15	1.228	779
52.3. Engineering creates new jobs so more people can have work	.64	.832	779
52.4. It is useful to know about engineering in my daily life	.28	1.012	779
52.5. Getting young people to understand engineering is important for our society	.43	.915	779
28.2. It is important to understand engineering even if you don't want an engineering job in the future	.35	.904	779
28.3. An engineering qualification can help you get many different types of job	.68	.879	779
39.7. ...Has explained to me that understanding engineering is useful for my future"	.03	1.064	779
51.4. My teachers explain how engineering qualifications can lead to different jobs	-.08	1.072	779
51.6. My teachers have explained to me that understanding engineering is useful for my future	-.31	1.084	779
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.	1.18	1.149	779
43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.	2.06	1.142	779
43.4. Read books or magazines about engineering?	.62	.910	779
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	1.10	1.271	779
44.1. Go to a museum?	1.38	.904	779
44.2. Go to a science centre, science museum, or planetarium?	1.10	.878	779
44.4. Do DIY, or help fix things around the home?	2.38	1.337	779
44.5. Get shown how to use tools?	2.25	1.344	779
44.6. Make models, e.g. playing with Lego, painting miniatures?	2.12	1.396	779
44.7. Do crafts, e.g. knitting, woodwork?	1.89	1.445	779

44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?	2.98	1.391	779
44.9. Program computers, e.g. writing apps, building websites?	1.23	1.384	779
45.2. Go to an after school club that involves engineering?	.26	.703	779
45.3. Had people visit you in school to teach you about engineering?	.65	.862	779
45.4. Take an engineering related school trip?	.39	.696	779
45.5. Take a school trip to a museum?	.81	.737	779
45.7. Take part in a competition where you design or make something?	.90	1.054	779
27.5. I would like to have a job that uses engineering	-.31	1.183	779
27.7. I want to become an engineer	-.74	1.094	779
27.6. People who are like me work in engineering	-.42	1.000	779
40.5. Other people think of me as an engineering-type person	-.70	1.044	779
51.5. My teachers have specifically encouraged me to consider studying engineering after GCSEs	-.65	.974	779
27.9. I would like to have a job that involves designing and making things	.14	1.158	779
27.10. I would like to work in an engineering related job, but not in an engineering industry	-.36	1.002	779

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.913
Bartlett's Test of Sphericity	Approx. Chi-Square	15421.453
	df	741
	Sig.	.000

Communalities

	Initial	Extraction
39.8. ...Know a lot about engineering"	1.000	.659
46.3. I have learnt a lot about engineering from museums	1.000	.620
52.2. Engineers need to be imaginative in their work	1.000	.749
39.5. ...Think that engineering is very interesting"	1.000	.768
39.6. ...Think it is important for me to learn about engineering"	1.000	.788
46.1. My family like going to museums	1.000	.742
46.2. I like going to museums	1.000	.725
52.3. Engineering creates new jobs so more people can have work	1.000	.747
52.4. It is useful to know about engineering in my daily life	1.000	.657
52.5. Getting young people to understand engineering is important for our society	1.000	.688
28.2. It is important to understand engineering even if you don't want an engineering job in the future	1.000	.727
28.3. An engineering qualification can help you get many different types of job	1.000	.705
39.7. ...Has explained to me that understanding engineering is useful for my future"	1.000	.775
51.4. My teachers explain how engineering qualifications can lead to different jobs	1.000	.792
51.6. My teachers have explained to me that understanding engineering is useful for my future	1.000	.849
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.	1.000	.707
43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.	1.000	.588
43.4. Read books or magazines about engineering?	1.000	.661
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	1.000	.653
44.1. Go to a museum?	1.000	.704
44.2. Go to a science centre, science museum, or planetarium?	1.000	.670
44.4. Do DIY, or help fix things around the home?	1.000	.712
44.5. Get shown how to use tools?	1.000	.695
44.6. Make models, e.g. playing with Lego, painting miniatures?	1.000	.605
44.7. Do crafts, e.g. knitting, woodwork?	1.000	.603
44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?	1.000	.670
44.9. Program computers, e.g. writing apps, building websites?	1.000	.487
45.2. Go to an after school club that involves engineering?	1.000	.546

45.3. Had people visit you in school to teach you about engineering?	1.000	.525
45.4. Take an engineering related school trip?	1.000	.664
45.5. Take a school trip to a museum?	1.000	.441
45.7. Take part in a competition where you design or make something?	1.000	.536
27.5. I would like to have a job that uses engineering	1.000	.821
27.7. I want to become an engineer	1.000	.764
27.6. People who are like me work in engineering	1.000	.646
40.5. Other people think of me as an engineering-type person	1.000	.644
51.5. My teachers have specifically encouraged me to consider studying engineering after GCSEs	1.000	.767
27.9. I would like to have a job that involves designing and making things	1.000	.549
27.10. I would like to work in an engineering related job, but not in an engineering industry	1.000	.632

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	10.725	27.500	27.500	10.725	27.500	27.500	5.654
2	3.420	8.769	36.269	3.420	8.769	36.269	4.709
3	2.274	5.830	42.099	2.274	5.830	42.099	4.545
4	2.002	5.133	47.232	2.002	5.133	47.232	3.347
5	1.702	4.364	51.596	1.702	4.364	51.596	3.430
6	1.532	3.927	55.523	1.532	3.927	55.523	5.641
7	1.344	3.447	58.970	1.344	3.447	58.970	5.352
8	1.193	3.058	62.029	1.193	3.058	62.029	4.468
9	1.067	2.737	64.766	1.067	2.737	64.766	2.613
10	1.023	2.622	67.388	1.023	2.622	67.388	3.623
11	.822	2.109	69.496				
12	.807	2.070	71.566				
13	.751	1.925	73.491				
14	.707	1.812	75.303				
15	.667	1.711	77.014				
16	.609	1.561	78.576				
17	.571	1.463	80.039				
18	.562	1.442	81.481				
19	.544	1.395	82.875				
20	.513	1.316	84.192				
21	.503	1.291	85.482				
22	.454	1.165	86.648				
23	.453	1.163	87.810				
24	.426	1.092	88.902				
25	.424	1.088	89.990				
26	.395	1.014	91.004				
27	.382	.979	91.983				
28	.366	.938	92.921				
29	.349	.894	93.816				
30	.329	.843	94.659				
31	.316	.811	95.470				
32	.288	.738	96.207				
33	.267	.683	96.891				
34	.251	.644	97.535				

35	.241	.619	98.153				
36	.217	.556	98.709				
37	.192	.491	99.201				
38	.157	.403	99.603				
39	.155	.397	100.000				

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Component Matrix[a]

	Component									
	1	2	3	4	5	6	7	8	9	10
40.5. Other people think of me as an engineering-type person	.696									
27.5. I would like to have a job that uses engineering	.689	-.404								
52.4. It is useful to know about engineering in my daily life	.676									
39.7. ...Has explained to me that understanding engineering is useful for my future"	.672									
39.6. ...Think it is important for me to learn about engineering"	.671									
39.5. ...Think that engineering is very interesting"	.667									
46.3. I have learnt a lot about engineering from museums	.664									
27.7. I want to become an engineer	.640	-.448								

43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	.616									
43.4. Read books or magazines about engineering?	.615									
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.	.607									
51.6. My teachers have explained to me that understanding engineering is useful for my future	.603			.520			-.425			
27.6. People who are like me work in engineering	.603									
52.5. Getting young people to understand engineering is important for our society	.601									
27.10. I would like to work in an engineering related job, but not in an engineering industry	.563									
51.5. My teachers have specifically encouraged me to consider studying engineering after GCSEs	.562			.468			-.450			

51.4. My teachers explain how engineering qualifications can lead to different jobs	.559			.482			-.434			
44.5. Get shown how to use tools?	.511				.467					
52.3. Engineering creates new jobs so more people can have work	.510		.410			.426				
44.6. Make models, e.g. playing with Lego, painting miniatures?	.509									
43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.	.465									
52.2. Engineers need to be imaginative in their work	.427									
27.9. I would like to have a job that involves designing and making things	.413									
45.2. Go to an after school club that involves engineering?										
44.2. Go to a science centre, science museum, or planetarium?	.463	.569								
44.1. Go to a museum?	.426	.560								
46.2. I like going to museums	.430	.459								
46.1. My family like going to museums	.403	.456	.436							

45.7. Take part in a competition where you design or make something?		.422								
45.5. Take a school trip to a museum?										
45.4. Take an engineering related school trip?				.517						
45.3. Had people visit you in school to teach you about engineering?				.436						
44.4. Do DIY, or help fix things around the home?	.431				.508					
44.7. Do crafts, e.g. knitting, woodwork?	.409				.439					
39.8. ...Know a lot about engineering"	.485					-.503				
44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?									.535	
44.9. Program computers, e.g. writing apps, building websites?										
28.2. It is important to understand engineering even if you don't want an engineering job in the future	.490									.568
28.3. An engineering qualification can help you get many different types of job	.486									.541

Extraction Method: Principal Component Analysis.

a. 10 components extracted.

Pattern Matrix[a]

	Component									
	1	2	3	4	5	6	7	8	9	10
27.10. I would like to work in an engineering related job, but not in an engineering industry	.767									
27.5. I would like to have a job that uses engineering	.761									
27.6. People who are like me work in engineering	.701									
27.7. I want to become an engineer	.698									
27.9. I would like to have a job that involves designing and making things	.673									
40.5. Other people think of me as an engineering-type person	.448									
46.1. My family like going to museums		.880								
46.2. I like going to museums		.842								
44.1. Go to a museum?		.810								
44.2. Go to a science centre, science museum, or planetarium?		.724								
46.3. I have learnt a lot about engineering from museums		.555								
52.2. Engineers need to be imaginative in their work			.897							

52.3. Engineering creates new jobs so more people can have work			.833							
52.5. Getting young people to understand engineering is important for our society			.633							
52.4. It is useful to know about engineering in my daily life			.513							
45.4. Take an engineering related school trip?				.797						
45.3. Had people visit you in school to teach you about engineering?				.661						
45.2. Go to an after school club that involves engineering?				.619						
45.5. Take a school trip to a museum?				.603						
45.7. Take part in a competition where you design or make something?				.458						
44.4. Do DIY, or help fix things around the home?					.820					
44.5. Get shown how to use tools?					.720					
44.7. Do crafts, e.g. knitting, woodwork?					.674					
44.6. Make models, e.g. playing with Lego, painting miniatures?					.459					

39.8. ...Know a lot about engineering"						-.845				
39.5. ...Think that engineering is very interesting"						-.777				
39.6. ...Think it is important for me to learn about engineering"						-.759				
39.7. ...Has explained to me that understanding engineering is useful for my future"						-.757				
51.6. My teachers have explained to me that understanding engineering is useful for my future							-.898			
51.4. My teachers explain how engineering qualifications can lead to different jobs							-.881			
51.5. My teachers have specifically encouraged me to consider studying engineering after GCSEs							-.859			
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.								-.705		

43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.							-.692		
43.4. Read books or magazines about engineering?							-.644		
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?							-.592		
44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?								.833	
44.9. Program computers, e.g. writing apps, building websites?								.622	
28.2. It is important to understand engineering even if you don't want an engineering job in the future									.816
28.3. An engineering qualification can help you get many different types of job									.788

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.[a]

a. Rotation converged in 12 iterations.

Structure Matrix

	Component									
	1	2	3	4	5	6	7	8	9	10
27.5. I would like to have a job that uses engineering	.873					-.462		-.400		
27.7. I want to become an engineer	.822					-.484		-.401		
27.10. I would like to work in an engineering related job, but not in an engineering industry	.783									
27.6. People who are like me work in engineering	.769									
40.5. Other people think of me as an engineering-type person	.660					-.548	-.450	-.489		
27.9. I would like to have a job that involves designing and making things	.657									
46.1. My family like going to museums		.849								
46.2. I like going to museums		.835								
44.1. Go to a museum?		.827								
44.2. Go to a science centre, science museum, or planetarium?		.785								
46.3. I have learnt a lot about engineering from museums		.673					-.457			
52.3. Engineering creates new jobs so more people can have work			.858							

52.2. Engineers need to be imaginative in their work			.846							
52.5. Getting young people to understand engineering is important for our society			.764							.506
52.4. It is useful to know about engineering in my daily life			.702			-.452	-.435			.519
45.4. Take an engineering related school trip?				.810						
45.3. Had people visit you in school to teach you about engineering?				.698						
45.2. Go to an after school club that involves engineering?				.657						
45.5. Take a school trip to a museum?				.622						
45.7. Take part in a competition where you design or make something?				.539	.474					
44.4. Do DIY, or help fix things around the home?					.827					
44.5. Get shown how to use tools?					.748					
44.7. Do crafts, e.g. knitting, woodwork?					.740					
44.6. Make models, e.g. playing with Lego, painting miniatures?					.603				.531	
39.6. ...Think it is important for me to learn about engineering"	.410					-.860				.452

39.7. ...Has explained to me that understanding engineering is useful for my future"						-.858	-.413			.401
39.5. ...Think that engineering is very interesting"						-.855				
39.8. ...Know a lot about engineering"						-.795				
51.6. My teachers have explained to me that understanding engineering is useful for my future							-.918			
51.4. My teachers explain how engineering qualifications can lead to different jobs							-.883			
51.5. My teachers have specifically encouraged me to consider studying engineering after GCSEs							-.863			
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.								-.799		
43.4. Read books or magazines about engineering?								-.764		
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	.459							-.721	.403	

43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.								-.715		
44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?									.809	
44.9. Program computers, e.g. writing apps, building websites?									.673	
28.2. It is important to understand engineering even if you don't want an engineering job in the future										.843
28.3. An engineering qualification can help you get many different types of job										.823

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Component Correlation Matrix

Component	1	2	3	4	5	6	7	8	9	10
1	1.000	.113	.246	.060	.130	-.347	-.315	-.288	.201	.244
2	.113	1.000	.228	.255	.247	-.148	-.203	-.215	.184	.131
3	.246	.228	1.000	.101	.143	-.312	-.287	-.150	.141	.310
4	.060	.255	.101	1.000	.157	-.120	-.271	-.200	.131	.018
5	.130	.247	.143	.157	1.000	-.129	-.184	-.198	.201	.050
6	-.347	-.148	-.312	-.120	-.129	1.000	.336	.255	-.048	-.335
7	-.315	-.203	-.287	-.271	-.184	.336	1.000	.226	-.175	-.278
8	-.288	-.215	-.150	-.200	-.198	.255	.226	1.000	-.198	-.161
9	.201	.184	.141	.131	.201	-.048	-.175	-.198	1.000	.045
10	.244	.131	.310	.018	.050	-.335	-.278	-.161	.045	1.000

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

A final PCA was then necessary to remove the two components (9 and 10) that did not meet the threshold of three items. Components with fewer than three items are difficult to interpret due to the lack of diversity of items. This third PCA was also found to be valid with a Kaiser-Meyer-Olkin (KMO) measure of 0.913 and a statistically significant Bartlett's test (p<0.001). This analysis resolved to eight components above an Eigenvalue of 1.0 that explained 66.213% of variance from a sample of 786 participants. These components are outlined in the table below. No further PCAs were necessary making this structure of eight components the 'simple structure' of this series of analyses.

Component Number	Component Label	Variance Explained	Items and Component Coefficients
1	Engineering Career Aspiration	28.758%	Six items: I would like to work in an engineering-related job, but not in an engineering industry (0.771) I would like to have a job that uses engineering (0.761) I would like to have a job that involves designing and making things (0.715) I want to become an engineer (0.695) People who are like me work in engineering (0.685) Other people think of me as an engineering-type person (0.429)
2	Museum Visits	9.505%	Five items: My family like going to museums (0.878) I like going to museums (0.841) Go to museum? (0.804) Go to a science centre, science museum, or planetarium? (0.719) I have learnt a lot about engineering from museums (0.558)
3	Engineering Utility	6.103%	Four items: Engineers need to be imaginative in their work (0.0.854) Engineering creates new jobs so more people can have work (0.849) Getting young people to understand engineering is important for our society (0.735) It is useful to know about engineering in my daily life (0.610)
4	Engineering Curricular-Mapped Experiences	5.713%	Five items: Take an engineering-related school trip? (0.795) Had people visit you in a school to teach you about engineering? (0.643) Go to an after school club that involves engineering? (0.629) Take a school trip to museum? (0.598)

			Take part in a competition where you design or make something? (0.499)
5	Making and Fixing	4.838%	Four items: Do DIY, or help fix things around the home (0.794) Get shown how to use tools? (0.688) Do crafts, e.g. knitting, woodwork? (0.677) Make models, e.g. playing with Lego, painting miniatures? (0.533)
6	Parental Engineering Attitudes	4.173%	Four items: …know a lot about engineering (0.806) …Think it is important for me to learn about engineering (0.764) …Think that engineering is very interesting (0.757) …Has explained to me that understanding engineering is useful for my future (0.751)
7	Teacher Support for Engineering	3.813%	Three items: My teachers have explained to me that understanding engineering is useful for my future (0.894) My teachers explain how engineering qualifications can lead to different jobs (0.873) My teachres have specifically encouraged me to consider studying engineering after GCSEs/National 5s (0.847)
8	Engineering Media Consumption	3.311%	Four items: Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc. (0.756) Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc (0.696) Read books or magazines about engineering? (0.690) Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games? (0.675)

PCA Three:

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
39.8. ...Know a lot about engineering"	-.05	1.142	786
46.3. I have learnt a lot about engineering from museums	-.61	1.109	786
52.2. Engineers need to be imaginative in their work	.74	.835	786
39.5. ...Think that engineering is very interesting"	.34	1.039	786
39.6. ...Think it is important for me to learn about engineering"	.12	1.004	786
46.1. My family like going to museums	.22	1.126	786
46.2. I like going to museums	.15	1.227	786
52.3. Engineering creates new jobs so more people can have work	.64	.830	786
52.4. It is useful to know about engineering in my daily life	.28	1.010	786
52.5. Getting young people to understand engineering is important for our society	.43	.913	786
39.7. ...Has explained to me that understanding engineering is useful for my future"	.03	1.062	786
51.4. My teachers explain how engineering qualifications can lead to different jobs	-.08	1.073	786
51.6. My teachers have explained to me that understanding engineering is useful for my future	-.31	1.082	786
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.	1.18	1.149	786
43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.	2.06	1.141	786
43.4. Read books or magazines about engineering?	.63	.913	786
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	1.10	1.268	786
44.1. Go to a museum?	1.39	.904	786
44.2. Go to a science centre, science museum, or planetarium?	1.10	.880	786
44.4. Do DIY, or help fix things around the home?	2.38	1.335	786
44.5. Get shown how to use tools?	2.25	1.342	786
44.6. Make models, e.g. playing with Lego, painting miniatures?	2.13	1.395	786
44.7. Do crafts, e.g. knitting, woodwork?	1.89	1.449	786
45.2. Go to an after school club that involves engineering?	.25	.700	786
45.3. Had people visit you in school to teach you about engineering?	.66	.872	786
45.4. Take an engineering related school trip?	.39	.696	786
45.5. Take a school trip to a museum?	.81	.735	786

45.7. Take part in a competition where you design or make something?	.90	1.054	786
27.5. I would like to have a job that uses engineering	-.31	1.181	786
27.7. I want to become an engineer	-.74	1.091	786
27.6. People who are like me work in engineering	-.42	.998	786
40.5. Other people think of me as an engineering-type person	-.71	1.045	786
51.5. My teachers have specifically encouraged me to consider studying engineering after GCSEs	-.66	.975	786
27.9. I would like to have a job that involves designing and making things	.14	1.156	786
27.10. I would like to work in an engineering related job, but not in an engineering industry	-.36	1.001	786

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.910
Bartlett's Test of Sphericity	Approx. Chi-Square	14496.568
	df	595
	Sig.	.000

Communalities

	Initial	Extraction
39.8. ...Know a lot about engineering"	1.000	.629
46.3. I have learnt a lot about engineering from museums	1.000	.622
52.2. Engineers need to be imaginative in their work	1.000	.673
39.5. ...Think that engineering is very interesting"	1.000	.753
39.6. ...Think it is important for me to learn about engineering"	1.000	.778
46.1. My family like going to museums	1.000	.741
46.2. I like going to museums	1.000	.726
52.3. Engineering creates new jobs so more people can have work	1.000	.727
52.4. It is useful to know about engineering in my daily life	1.000	.653
52.5. Getting young people to understand engineering is important for our society	1.000	.680
39.7. ...Has explained to me that understanding engineering is useful for my future"	1.000	.766
51.4. My teachers explain how engineering qualifications can lead to different jobs	1.000	.786
51.6. My teachers have explained to me that understanding engineering is useful for my future	1.000	.847
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.	1.000	.706
43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.	1.000	.552
43.4. Read books or magazines about engineering?	1.000	.662
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	1.000	.640
44.1. Go to a museum?	1.000	.699
44.2. Go to a science centre, science museum, or planetarium?	1.000	.668
44.4. Do DIY, or help fix things around the home?	1.000	.682
44.5. Get shown how to use tools?	1.000	.661
44.6. Make models, e.g. playing with Lego, painting miniatures?	1.000	.548
44.7. Do crafts, e.g. knitting, woodwork?	1.000	.595
45.2. Go to an after school club that involves engineering?	1.000	.541
45.3. Had people visit you in school to teach you about engineering?	1.000	.501
45.4. Take an engineering related school trip?	1.000	.664
45.5. Take a school trip to a museum?	1.000	.418
45.7. Take part in a competition where you design or make something?	1.000	.497
27.5. I would like to have a job that uses engineering	1.000	.819
27.7. I want to become an engineer	1.000	.762
27.6. People who are like me work in engineering	1.000	.624
40.5. Other people think of me as an engineering-type person	1.000	.637
51.5. My teachers have specifically encouraged me to consider studying engineering after GCSEs	1.000	.759
27.9. I would like to have a job that involves designing and making things	1.000	.528
27.10. I would like to work in an engineering related job, but not in an engineering industry	1.000	.632

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	10.065	28.758	28.758	10.065	28.758	28.758	5.467
2	3.327	9.505	38.263	3.327	9.505	38.263	4.555
3	2.136	6.103	44.366	2.136	6.103	44.366	4.776
4	1.999	5.713	50.079	1.999	5.713	50.079	3.312
5	1.693	4.838	54.917	1.693	4.838	54.917	3.287
6	1.461	4.173	59.090	1.461	4.173	59.090	5.191
7	1.334	3.813	62.902	1.334	3.813	62.902	5.051
8	1.159	3.311	66.213	1.159	3.311	66.213	4.998
9	.852	2.434	68.648				
10	.753	2.152	70.800				
11	.740	2.115	72.915				
12	.714	2.040	74.954				
13	.642	1.835	76.789				
14	.618	1.765	78.554				
15	.580	1.656	80.210				
16	.569	1.627	81.837				
17	.511	1.460	83.297				
18	.506	1.447	84.743				
19	.482	1.376	86.120				
20	.444	1.268	87.388				
21	.439	1.255	88.643				
22	.404	1.155	89.798				
23	.386	1.104	90.902				
24	.375	1.071	91.973				
25	.356	1.016	92.989				
26	.341	.974	93.962				
27	.321	.918	94.880				
28	.288	.824	95.704				
29	.270	.773	96.477				
30	.256	.733	97.209				
31	.246	.702	97.912				
32	.218	.623	98.535				
33	.197	.562	99.096				
34	.162	.461	99.558				
35	.155	.442	100.000				

Component Matrix^{a}

	Component							
	1	2	3	4	5	6	7	8
40.5. Other people think of me as an engineering-type person	.702							
27.5. I would like to have a job that uses engineering	.686	-.440						
39.7. ...Has explained to me that understanding engineering is useful for my future"	.672							
52.4. It is useful to know about engineering in my daily life	.668							
46.3. I have learnt a lot about engineering from museums	.667							
39.6. ...Think it is important for me to learn about engineering"	.667							
39.5. ...Think that engineering is very interesting"	.667							
27.7. I want to become an engineer	.636	-.483						
43.4. Read books or magazines about engineering?	.620							
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	.615							
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.	.612							

51.6. My teachers have explained to me that understanding engineering is useful for my future	.607			.519			-.423	
27.6. People who are like me work in engineering	.603							
52.5. Getting young people to understand engineering is important for our society	.591							
51.5. My teachers have specifically encouraged me to consider studying engineering after GCSEs	.568			.463			-.438	
27.10. I would like to work in an engineering related job, but not in an engineering industry	.563							
51.4. My teachers explain how engineering qualifications can lead to different jobs	.560			.488			-.437	
44.5. Get shown how to use tools?	.510				.498			
52.3. Engineering creates new jobs so more people can have work	.502		-.461			.432		
44.6. Make models, e.g. playing with Lego, painting miniatures?	.499							
43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.	.465							-.416

52.2. Engineers need to be imaginative in their work	.428					.428		
27.9. I would like to have a job that involves designing and making things	.410							
45.2. Go to an after school club that involves engineering?	.409							
44.2. Go to a science centre, science museum, or planetarium?	.469	.582						
44.1. Go to a museum?	.433	.577						
46.1. My family like going to museums	.408	.500						
46.2. I like going to museums	.434	.493						
45.7. Take part in a competition where you design or make something?								
45.5. Take a school trip to a museum?								
45.4. Take an engineering related school trip?				.510				
45.3. Had people visit you in school to teach you about engineering?				.433				
44.4. Do DIY, or help fix things around the home?	.433				.524			
44.7. Do crafts, e.g. knitting, woodwork?	.408				.444			
39.8. ...Know a lot about engineering"	.493					-.526		

Extraction Method: Principal Component Analysis.

a. 8 components extracted.

Pattern Matrix[a]

	Component							
	1	2	3	4	5	6	7	8
27.10. I would like to work in an engineering related job, but not in an engineering industry	.771							
27.5. I would like to have a job that uses engineering	.761							
27.9. I would like to have a job that involves designing and making things	.715							
27.7. I want to become an engineer	.695							
27.6. People who are like me work in engineering	.685							
40.5. Other people think of me as an engineering-type person	.429							
46.1. My family like going to museums		.878						
46.2. I like going to museums		.841						
44.1. Go to a museum?		.804						
44.2. Go to a science centre, science museum, or planetarium?		.719						
46.3. I have learnt a lot about engineering from museums		.558						
52.2. Engineers need to be imaginative in their work			-.854					
52.3. Engineering creates new jobs so more people can have work			-.849					

52.5. Getting young people to understand engineering is important for our society			-.735					
52.4. It is useful to know about engineering in my daily life			-.610					
45.4. Take an engineering related school trip?				.795				
45.3. Had people visit you in school to teach you about engineering?				.643				
45.2. Go to an after school club that involves engineering?				.629				
45.5. Take a school trip to a museum?				.598				
45.7. Take part in a competition where you design or make something?				.499	.410			
44.4. Do DIY, or help fix things around the home?					.794			
44.5. Get shown how to use tools?					.688			
44.7. Do crafts, e.g. knitting, woodwork?					.677			
44.6. Make models, e.g. playing with Lego, painting miniatures?					.533			
39.8. ...Know a lot about engineering"						-.806		
39.6. ...Think it is important for me to learn about engineering"						-.764		
39.5. ...Think that engineering is very interesting"						-.757		

39.7. ...Has explained to me that understanding engineering is useful for my future"						-.751		
51.6. My teachers have explained to me that understanding engineering is useful for my future							-.894	
51.4. My teachers explain how engineering qualifications can lead to different jobs							-.873	
51.5. My teachers have specifically encouraged me to consider studying engineering after GCSEs							-.847	
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.								-.756
43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.								-.696
43.4. Read books or magazines about engineering?								-.690
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?								-.675

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.[a]

a. Rotation converged in 10 iterations.

Structure Matrix

	Component							
	1	2	3	4	5	6	7	8
27.5. I would like to have a job that uses engineering	.873					-.460		-.442
27.7. I want to become an engineer	.819					-.482		-.434
27.10. I would like to work in an engineering related job, but not in an engineering industry	.786							
27.6. People who are like me work in engineering	.766							
27.9. I would like to have a job that involves designing and making things	.671							
40.5. Other people think of me as an engineering-type person	.654					-.544	-.449	-.512
46.1. My family like going to museums		.851						
46.2. I like going to museums		.838						
44.1. Go to a museum?		.823						
44.2. Go to a science centre, science museum, or planetarium?		.782						
46.3. I have learnt a lot about engineering from museums		.675					-.454	-.401
52.3. Engineering creates new jobs so more people can have work			-.848					
52.2. Engineers need to be imaginative in their work			-.807					

52.5. Getting young people to understand engineering is important for our society			-.806					
52.4. It is useful to know about engineering in my daily life			-.753			-.451	-.444	
45.4. Take an engineering related school trip?				.810				
45.3. Had people visit you in school to teach you about engineering?				.687				
45.2. Go to an after school club that involves engineering?				.656				-.407
45.5. Take a school trip to a museum?				.617				
45.7. Take part in a competition where you design or make something?				.563	.488			
44.4. Do DIY, or help fix things around the home?					.808			
44.7. Do crafts, e.g. knitting, woodwork?					.738			
44.5. Get shown how to use tools?					.722	-.408		
44.6. Make models, e.g. playing with Lego, painting miniatures?					.643			-.420
39.6. ...Think it is important for me to learn about engineering"	.415		-.419			-.858		
39.7. ...Has explained to me that understanding engineering is useful for my future"			-.415			-.849	-.413	
39.5. ...Think that engineering is very interesting"			-.430			-.842		

39.8. ...Know a lot about engineering"						-.781		
51.6. My teachers have explained to me that understanding engineering is useful for my future							-.917	
51.4. My teachers explain how engineering qualifications can lead to different jobs							-.881	
51.5. My teachers have specifically encouraged me to consider studying engineering after GCSEs							-.862	
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.								-.822
43.4. Read books or magazines about engineering?								-.786
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	.459							-.765
43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.								-.705

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Binary Logistic Regression: Formation of Engineering Capital Instrument

A binary logistic regression was adopted to identify items that were most predictive of engineering aspirations as a proxy for engineering capital. Statistical assumptions were tested and confirmed the linearity of the relationship between IVs and DV logit (Box-Tidwell test), a lack of significant multicollinearity (collinearity VIF <5) and a lack of influential outliers supporting the adoption of this procedure (casewise diagnostics). The logistic regression model was statistically significant, χ2(41) = 400.798, p<0.001, supporting the adoption of its predictive IVs as effective distinguishing items that delineate those with greater or lesser aspiration to engineering futures. These items are outlined in the Chapter Eight.

Box-Tidwell test of linearity:

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	39.8. ...Know a lot about engineering"	.106	.302	.123	1	.726	1.111
	39.8. ...Know a lot about engineering" by STANDARD39.8	-.080	.090	.788	1	.375	.923
	46.3. I have learnt a lot about engineering from museums	.401	.279	2.073	1	.150	1.494
	46.3. I have learnt a lot about engineering from museums by STANDARD46.3	-.036	.111	.106	1	.745	.965
	40.6. I know how to design and make things	.153	.365	.176	1	.675	1.166
	40.6. I know how to design and make things by STANDARD40.6	.015	.103	.021	1	.884	1.015
	40.7. I know quite a lot about engineering	.645	.352	3.364	1	.067	1.906
	40.7. I know quite a lot about engineering by STANDARD40.7	-.077	.154	.248	1	.619	.926
	52.2. Engineers need to be imaginative in their work	-.214	.695	.095	1	.758	.808
	52.2. Engineers need to be imaginative in their work by STANDARD52.2	.056	.163	.118	1	.731	1.058
	40.8. I would be confident talking about engineering in lessons	.283	.292	.939	1	.333	1.327
	40.8. I would be confident talking about engineering in lessons by STANDARD40.8	.003	.126	.001	1	.980	1.003
	39.5. ...Think that engineering is very interesting"	.956	.518	3.412	1	.065	2.602
	39.5. ...Think that engineering is very interesting" by STANDARD39.5	-.189	.139	1.865	1	.172	.827
	39.6. ...Think it is important for me to learn about engineering"	.460	.533	.746	1	.388	1.584
	39.6. ...Think it is important for me to learn about engineering" by STANDARD39.6	-.075	.155	.235	1	.628	.928
	46.1. My family like going to museums	-.513	.337	2.317	1	.128	.599
	46.1. My family like going to museums by STANDARD46.1	.113	.096	1.377	1	.241	1.119
	46.2. I like going to museums	.112	.318	.125	1	.723	1.119
	46.2. I like going to museums by STANDARD46.2	-.071	.095	.551	1	.458	.932

	52.3. Engineering creates new jobs so more people can have work	-.184	.825	.050	1	.824	.832
	52.3. Engineering creates new jobs so more people can have work by STANDARD52.3	.053	.192	.077	1	.781	1.055
	52.4. It is useful to know about engineering in my daily life	.458	.496	.853	1	.356	1.581
	52.4. It is useful to know about engineering in my daily life by STANDARD52.4	-.053	.140	.142	1	.707	.949
	52.5. Getting young people to understand engineering is important for our society	.500	.624	.642	1	.423	1.649
	52.5. Getting young people to understand engineering is important for our society by STANDARD52.5	-.082	.156	.273	1	.601	.922
	28.2. It is important to understand engineering even if you don't want an engineering job in the future	-.542	.472	1.317	1	.251	.582
	28.2. It is important to understand engineering even if you don't want an engineering job in the future by STANDARD28.2	.083	.130	.408	1	.523	1.086
	28.3. An engineering qualification can help you get many different types of job	.787	.539	2.133	1	.144	2.196
	28.3. An engineering qualification can help you get many different types of job by STANDARD28.3	-.073	.130	.313	1	.576	.930
	39.7. ...Has explained to me that understanding engineering is useful for my future"	-.266	.451	.349	1	.555	.766
	39.7. ...Has explained to me that understanding engineering is useful for my future" by STANDARD39.7	.155	.140	1.216	1	.270	1.167
	51.4. My teachers explain how engineering qualifications can lead to different jobs	.101	.485	.044	1	.835	1.106
	51.4. My teachers explain how engineering qualifications can lead to different jobs by STANDARD51.4	-.053	.143	.137	1	.711	.948
	51.6. My teachers have explained to me that understanding engineering is useful for my future	-.075	.307	.059	1	.808	.928
	51.6. My teachers have explained to me that understanding engineering is useful for my future by STANDARD51.6	.012	.111	.012	1	.913	1.012
	31. When you are not in school how often do you talk about engineering with other people?	.615	.381	2.601	1	.107	1.849
	31. When you are not in school how often do you talk about engineering with other people? by STANDARD31	-.065	.094	.479	1	.489	.937
	43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.	-.172	.414	.174	1	.677	.842
	43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc. by STANDARD43.2	.079	.105	.570	1	.450	1.083

	43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.	.412	.426	.933	1	.334	1.509
	43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc. by STANDARD43.3	-.119	.086	1.937	1	.164	.888
	43.4. Read books or magazines about engineering?	-.456	.682	.447	1	.504	.634
	43.4. Read books or magazines about engineering? by STANDARD43.4	.301	.225	1.791	1	.181	1.351
	43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	.759	.391	3.764	1	.052	2.136
	43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games? by STANDARD43.5	-.108	.090	1.418	1	.234	.898
	39.1. ...Sign me up to activities outside of school time (e.g. dance, music, clubs)"	.221	.302	.536	1	.464	1.248
	39.1. ...Sign me up to activities outside of school time (e.g. dance, music, clubs)" by STANDARD39.1	-.088	.082	1.165	1	.280	.916
	44.1. Go to a museum?	-.245	.622	.155	1	.694	.783
	44.1. Go to a museum? by STANDARD44.1	.031	.150	.042	1	.837	1.031
	44.2. Go to a science centre, science museum, or planetarium?	-.240	.594	.163	1	.686	.786
	44.2. Go to a science centre, science museum, or planetarium? by STANDARD44.2	.069	.164	.176	1	.675	1.071
	44.4. Do DIY, or help fix things around the home?	-.075	.409	.033	1	.855	.928
	44.4. Do DIY, or help fix things around the home? by STANDARD44.4	.059	.077	.588	1	.443	1.061
	44.5. Get shown how to use tools?	.355	.392	.823	1	.364	1.427
	44.5. Get shown how to use tools? by STANDARD44.5	-.082	.077	1.138	1	.286	.922
	44.6. Make models, e.g. playing with Lego, painting miniatures?	-.374	.391	.915	1	.339	.688
	44.6. Make models, e.g. playing with Lego, painting miniatures? by STANDARD44.6	.093	.073	1.611	1	.204	1.097
	44.7. Do crafts, e.g. knitting, woodwork?	-.033	.372	.008	1	.928	.967
	44.7. Do crafts, e.g. knitting, woodwork? by STANDARD44.7	.001	.088	.000	1	.991	1.001
	44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?	-.161	.423	.145	1	.703	.851
	44.8. Play videogames about designing or building, e.g. The Sims, Minecraft? by STANDARD44.8	.057	.076	.554	1	.457	1.058
	44.7. Do crafts, e.g. knitting, woodwork? by STANDARD44.7REAL	-.072	.074	.938	1	.333	.931

	44.9. Program computers, e.g. writing apps, building websites?	-.337	.350	.925	1	.336	.714
	44.9. Program computers, e.g. writing apps, building websites? by STANDARD44.9	.073	.075	.944	1	.331	1.076
	45.2. Go to an after school club that involves engineering?	1.714	.656	6.832	1	.009	5.550
	45.2. Go to an after school club that involves engineering? by STANDARD45.2	-.371	.161	5.313	1	.021	.690
	45.3. Had people visit you in school to teach you about engineering?	.436	.563	.601	1	.438	1.547
	45.3. Had people visit you in school to teach you about engineering? by STANDARD45.3	-.115	.171	.448	1	.503	.892
	45.4. Take an engineering related school trip?	-1.430	.647	4.878	1	.027	.239
	45.4. Take an engineering related school trip? by STANDARD45.4	.327	.210	2.428	1	.119	1.387
	45.5. Take a school trip to a museum?	.040	.525	.006	1	.940	1.040
	45.5. Take a school trip to a museum? by STANDARD45.5	-.110	.164	.453	1	.501	.896
	45.6. Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes	.341	.380	.805	1	.370	1.407
	45.6. Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes by STANDARD45.6	-.068	.082	.690	1	.406	.934
	45.7. Take part in a competition where you design or make something?	.059	.413	.020	1	.887	1.061
	45.7. Take part in a competition where you design or make something? by STANDARD45.7	-.027	.112	.057	1	.811	.974
	Constant	-.013	.617	.000	1	.983	.987

Linear regression test of collinearity:

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	39.8. ...Know a lot about engineering"	.502	1.994
	46.3. I have learnt a lot about engineering from museums	.445	2.246
	40.6. I know how to design and make things	.590	1.696
	40.7. I know quite a lot about engineering	.305	3.276
	52.2. Engineers need to be imaginative in their work	.533	1.876
	40.8. I would be confident talking about engineering in lessons	.361	2.772
	39.5. ...Think that engineering is very interesting"	.328	3.053
	39.6. ...Think it is important for me to learn about engineering"	.253	3.959
	46.1. My family like going to museums	.358	2.793
	46.2. I like going to museums	.353	2.836
	52.3. Engineering creates new jobs so more people can have work	.463	2.160
	52.4. It is useful to know about engineering in my daily life	.346	2.888
	52.5. Getting young people to understand engineering is important for our society	.384	2.605
	28.2. It is important to understand engineering even if you don't want an engineering job in the future	.634	1.577
	28.3. An engineering qualification can help you get many different types of job	.627	1.596
	39.7. ...Has explained to me that understanding engineering is useful for my future"	.264	3.792
	51.4. My teachers explain how engineering qualifications can lead to different jobs	.407	2.458
	51.6. My teachers have explained to me that understanding engineering is useful for my future	.373	2.684
	31. When you are not in school how often do you talk about engineering with other people?	.398	2.513
	TOTAL KNOWING SOMEONE ENGINEERING	.353	2.833
	35. Do you know anyone (family, friends, or community) who works as an engineer or in a job that uses engineering?	.395	2.531
	AS Eng Cap Talk with Engineering	.467	2.143
	43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.	.446	2.241
	43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.	.616	1.622
	43.4. Read books or magazines about engineering?	.472	2.117
	43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	.490	2.041

	39.1. ...Sign me up to activities outside of school time (e.g. dance, music, clubs)"	.805	1.242
	44.1. Go to a museum?	.342	2.924
	44.2. Go to a science centre, science museum, or planetarium?	.356	2.807
	44.4. Do DIY, or help fix things around the home?	.498	2.007
	44.5. Get shown how to use tools?	.458	2.185
	44.6. Make models, e.g. playing with Lego, painting miniatures?	.509	1.963
	44.7. Do crafts, e.g. knitting, woodwork?	.560	1.784
	44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?	.751	1.332
	44.9. Program computers, e.g. writing apps, building websites?	.732	1.367
	45.2. Go to an after school club that involves engineering?	.654	1.530
	45.3. Had people visit you in school to teach you about engineering?	.616	1.624
	45.4. Take an engineering related school trip?	.553	1.808
	45.5. Take a school trip to a museum?	.722	1.385
	45.6. Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes	.660	1.515
	45.7. Take part in a competition where you design or make something?	.639	1.565

Binary Logistic Regression:

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	648	70.4
	Missing Cases	273	29.6
	Total	921	100.0
Unselected Cases		0	.0
Total		921	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
Lower	0
Higher	1

Classification Table[a,b]

			Predicted		
			EngCapDV		Percentage
	Observed		Lower	Higher	Correct
Step 0	EngCapDV	Lower	0	295	.0
		Higher	0	353	100.0
	Overall Percentage				54.5

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	.179	.079	5.177	1	.023	1.197

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	400.798	41	<.001
	Block	400.798	41	<.001
	Model	400.798	41	<.001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	492.322[a]	.461	.617

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	9.324	8	.316

Classification Table[a]

			Predicted		
			EngCapDV		Percentage Correct
Observed			Lower	Higher	
Step 1	EngCapDV	Lower	235	60	79.7
		Higher	61	292	82.7
	Overall Percentage				81.3

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	39.8. ...Know a lot about engineering"	-.048	.136	.124	1	.725	.953
	46.3. I have learnt a lot about engineering from museums	.411	.158	6.768	1	.009	1.508
	40.6. I know how to design and make things	.308	.142	4.692	1	.030	1.360
	40.7. I know quite a lot about engineering	.473	.194	5.940	1	.015	1.606
	52.2. Engineers need to be imaginative in their work	.037	.197	.035	1	.851	1.038
	40.8. I would be confident talking about engineering in lessons	.340	.168	4.079	1	.043	1.405
	39.5. ...Think that engineering is very interesting"	.262	.177	2.187	1	.139	1.300
	39.6. ...Think it is important for me to learn about engineering"	.154	.218	.502	1	.479	1.167
	46.1. My family like going to museums	.106	.175	.370	1	.543	1.112
	46.2. I like going to museums	-.306	.161	3.593	1	.058	.737
	52.3. Engineering creates new jobs so more people can have work	.083	.209	.159	1	.690	1.087
	52.4. It is useful to know about engineering in my daily life	.352	.194	3.288	1	.070	1.422
	52.5. Getting young people to understand engineering is important for our society	-.015	.199	.006	1	.938	.985
	28.2. It is important to understand engineering even if you don't want an engineering job in the future	-.309	.161	3.698	1	.054	.734

28.3. An engineering qualification can help you get many different types of job	.505	.168	9.079	1	.003	1.657
39.7. ...Has explained to me that understanding engineering is useful for my future"	.216	.196	1.214	1	.270	1.241
51.4. My teachers explain how engineering qualifications can lead to different jobs	-.181	.171	1.117	1	.291	.835
51.6. My teachers have explained to me that understanding engineering is useful for my future	.085	.175	.235	1	.628	1.089
31. When you are not in school how often do you talk about engineering with other people?	.364	.138	6.929	1	.008	1.439
TOTAL KNOWING SOMEONE ENGINEERING	-.162	.200	.654	1	.419	.851
35. Do you know anyone (family, friends, or community) who works as an engineer or in a job that uses engineering?	-.117	.381	.095	1	.758	.889
AS Eng Cap Talk with Engineering	.052	.265	.039	1	.844	1.054
43.2. Watch engineering TV programmes, e.g. Mythbusters, Scrapheap Challenge, Robot Wars, etc.	-.028	.150	.036	1	.849	.972
43.3. Watch TV programmes with some engineering in them, e.g. Blue Peter, The Big Bang Theory, Top Gear, The Great British Bake Off, etc.	-.216	.127	2.875	1	.090	.806
43.4. Read books or magazines about engineering?	.526	.215	5.989	1	.014	1.691
43.5. Go online to find out about engineering, e.g. YouTube, engineering websites, play engineering games?	.411	.135	9.296	1	.002	1.508
39.1. ...Sign me up to activities outside of school time (e.g. dance, music, clubs)"	-.140	.109	1.639	1	.200	.869
44.1. Go to a museum?	-.098	.236	.174	1	.677	.906
44.2. Go to a science centre, science museum, or planetarium?	.019	.225	.007	1	.932	1.019
44.4. Do DIY, or help fix things around the home?	.274	.118	5.427	1	.020	1.316
44.5. Get shown how to use tools?	-.075	.123	.379	1	.538	.927
44.6. Make models, e.g. playing with Lego, painting miniatures?	.050	.110	.203	1	.653	1.051
44.7. Do crafts, e.g. knitting, woodwork?	-.313	.107	8.579	1	.003	.731

	44.8. Play videogames about designing or building, e.g. The Sims, Minecraft?	.130	.095	1.883	1	.170	1.139
	44.9. Program computers, e.g. writing apps, building websites?	-.044	.098	.199	1	.655	.957
	45.2. Go to an after school club that involves engineering?	.324	.248	1.703	1	.192	1.383
	45.3. Had people visit you in school to teach you about engineering?	.080	.177	.205	1	.651	1.083
	45.4. Take an engineering related school trip?	-.537	.232	5.360	1	.021	.585
	45.5. Take a school trip to a museum?	-.219	.177	1.533	1	.216	.803
	45.6. Do school activities where you design or build something, e.g. designing a bridge, making and testing paper airplanes	.029	.115	.064	1	.800	1.030
	45.7. Take part in a competition where you design or make something?	.007	.141	.002	1	.962	1.007
	Constant	.080	.502	.026	1	.873	1.084

Directory of Statistical Analyses Outputs for Chapter Seven

Independent Samples T-Test: Engineering Educational Aspiration and Engineering Capital Score

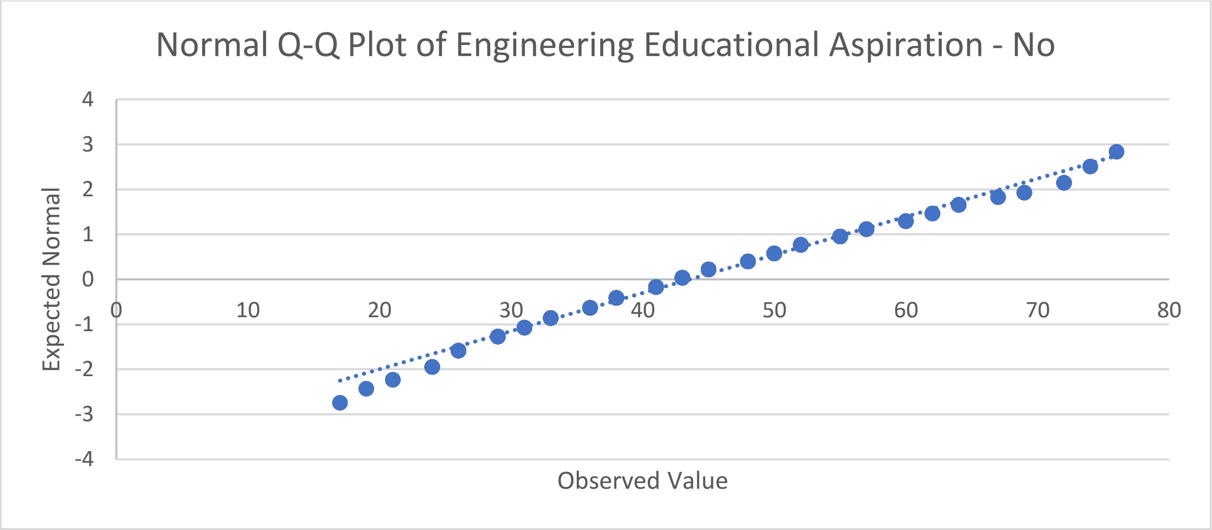
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1. The assumptions underpinning this test were met approving its use.

Case Processing Summary

	Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no	Cases					
		Valid		Missing		Total	
		N	Percent	N	Percent	N	Percent
Engineering Capital Score	No	659	100.0%	0	0.0%	659	100.0%
	Yes	228	100.0%	0	0.0%	228	100.0%

Descriptives

			Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no			
			No		Yes	
			Statistic	Std. Error	Statistic	Std. Error
Engineering Capital Score	Mean		43.5751	.45168	60.9518	.89708
	95% Confidence Interval for Mean	Lower Bound	42.6882		59.1841	
		Upper Bound	44.4620		62.7194	
	5% Trimmed Mean		43.2870		60.9805	
	Median		43.0000		60.0000	
	Variance		134.448		183.482	
	Std. Deviation		11.59519		13.54556	
	Minimum		17.00		24.00	
	Maximum		76.00		95.00	
	Range		59.00		71.00	
	Interquartile Range		14.00		17.00	
	Skewness		.338	.095	.001	.161
	Kurtosis		-.213	.190	-.160	.321


Normal Q-Q Plot of Engineering Educational Aspiration - No
Expected Normal
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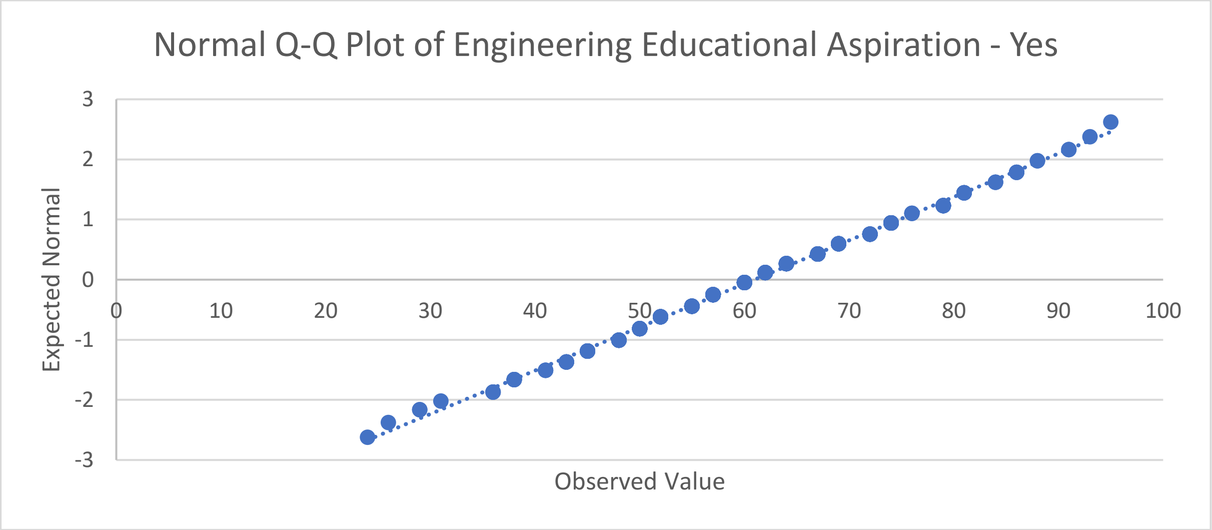
3
2
1
0
-1
-2
-3
-4
0
10
20
30
40
50
60
70
80
Observed Value


Normal Q-Q Plot of Engineering Educational Aspiration - Yes
Expected Normal
3
2
1
0
-1
-2
-3
0
10
20
30
40
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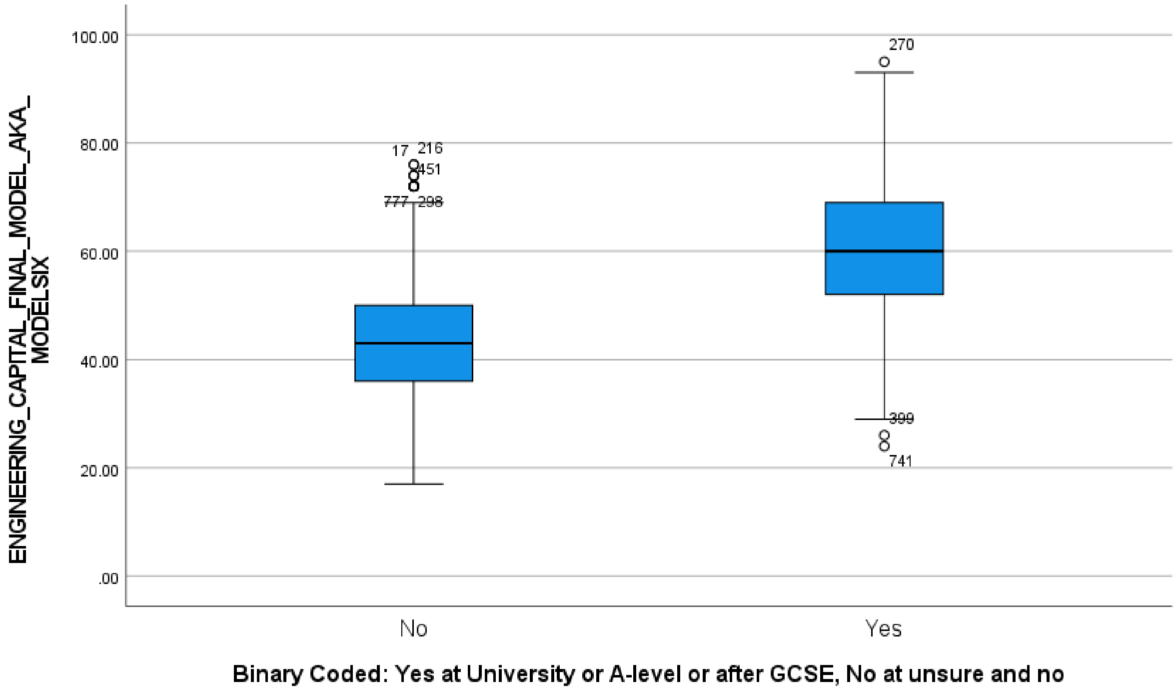
60
70
80
90
100
Observed Value


ENGINEERING_CAPITAL_FINAL_MODEL_AKA_MODELSIX
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80.00
60.00
40.00
20.00
.00
17
216
451
777
298
270
399
741
No
Yes
Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no

A Welch's independent samples t-test identified a significant difference in the engineering capital scores of those who did (M=60.95, SD=13.55) and did not wish to study engineering (M=43.58, SD=11.60) (t(348.950)=17.301, p<0.001, d=1.433). The Cohen's d effect size highlights a strong effect of educational aspiration on engineering capital scores.

Group Statistics

	Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no	N	Mean	Std. Deviation	Std. Error Mean
Eng. Cap. Score.	No	659	43.5751	11.59519	.45168
	Yes	228	60.9518	13.54556	.89708

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Eng. Cap. Score.	Equal variances assumed	7.681	.006	-18.652	885	<.001	<.001	-17.37664	.93164	-19.20512	-15.54816
	Equal variances not assumed			-17.301	348.950	<.001	<.001	-17.37664	1.00437	-19.35203	-15.40125

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
Eng. Cap. Score.	Cohen's d	12.12540	-1.433	-1.597	-1.268
	Hedges' correction	12.13569	-1.432	-1.596	-1.267
	Glass's delta	13.54556	-1.283	-1.473	-1.091

One-Way ANOVA: Engineering Educational Aspiration and Engineering Capital Score

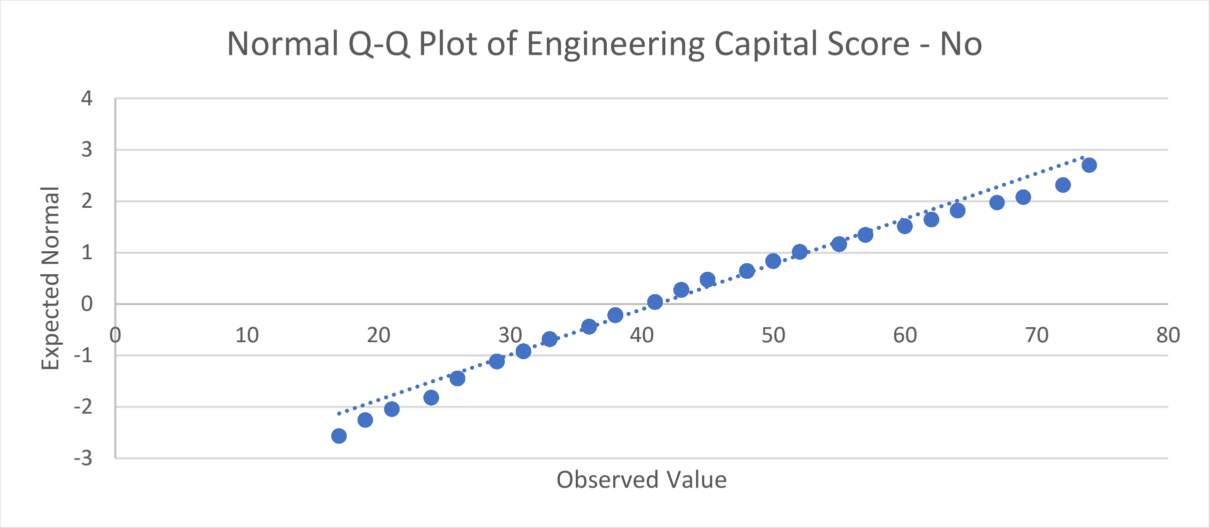
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1. The assumptions underpinning this test were met approving its use.

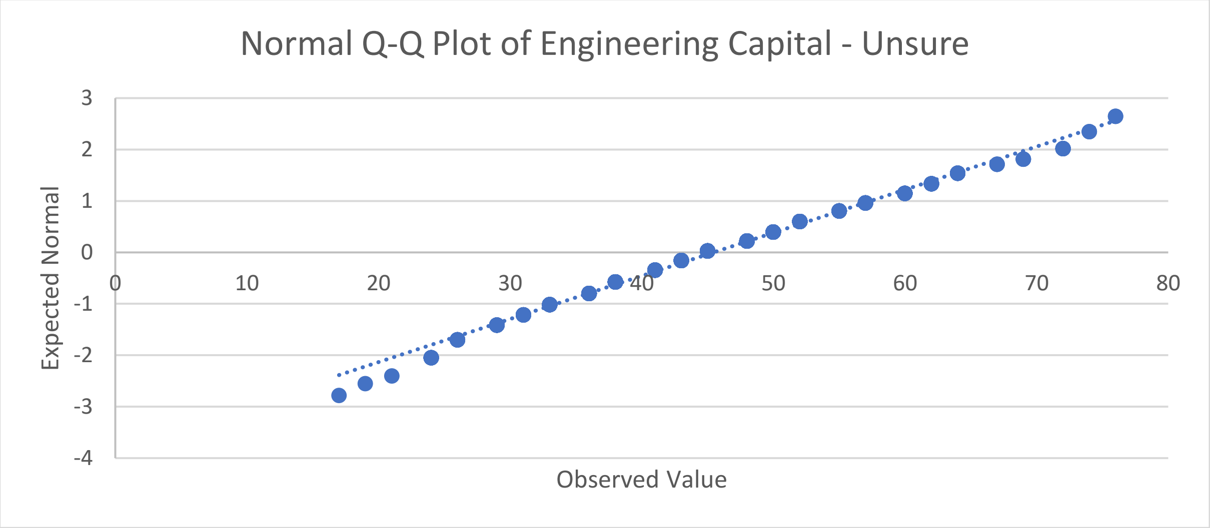
Case Processing Summary

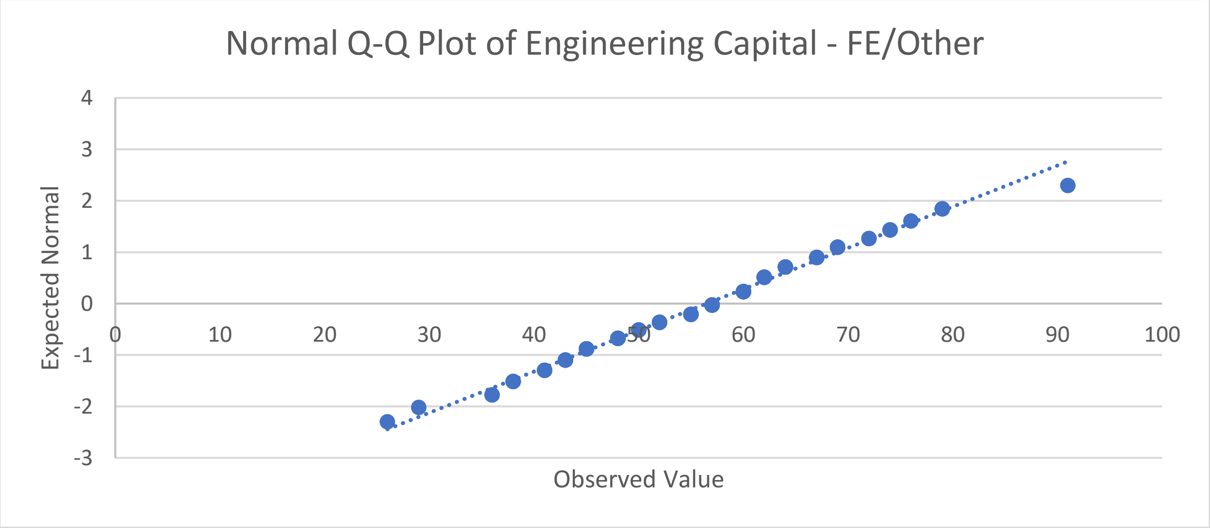
	Engineering Educational Aspiration	Cases					
		Valid		Missing		Total	
		N	Percent	N	Percent	N	Percent
Engineering Capital Score	No	290	100.0%	0	0.0%	290	100.0%
	Unsure	369	100.0%	0	0.0%	369	100.0%
	Yes- FEOther	91	100.0%	0	0.0%	91	100.0%
	Yes – FEAcadem.	63	100.0%	0	0.0%	63	100.0%
	Yes - University	74	100.0%	0	0.0%	74	100.0%

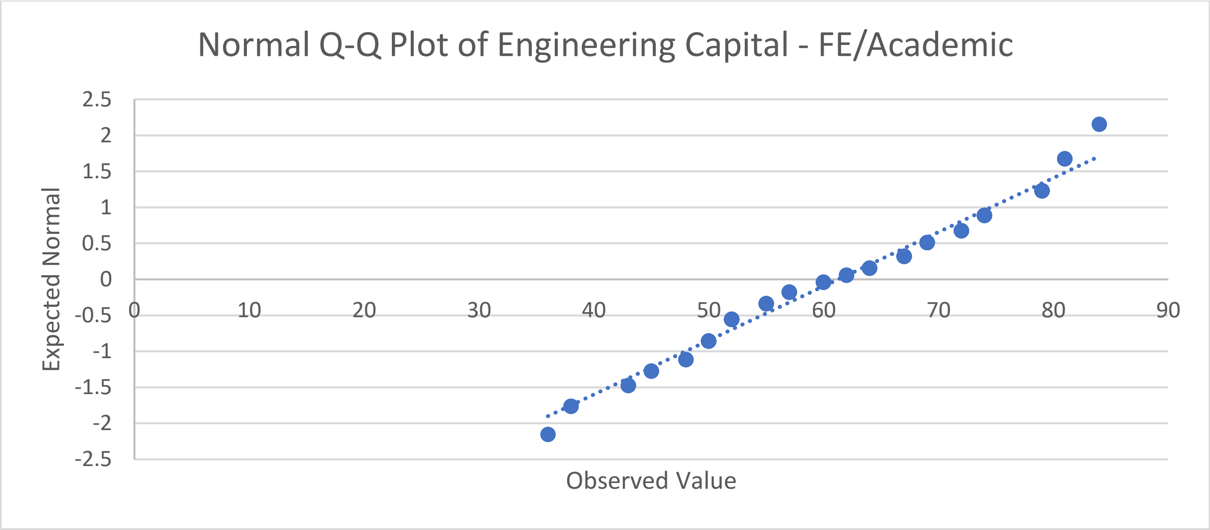
Descriptives

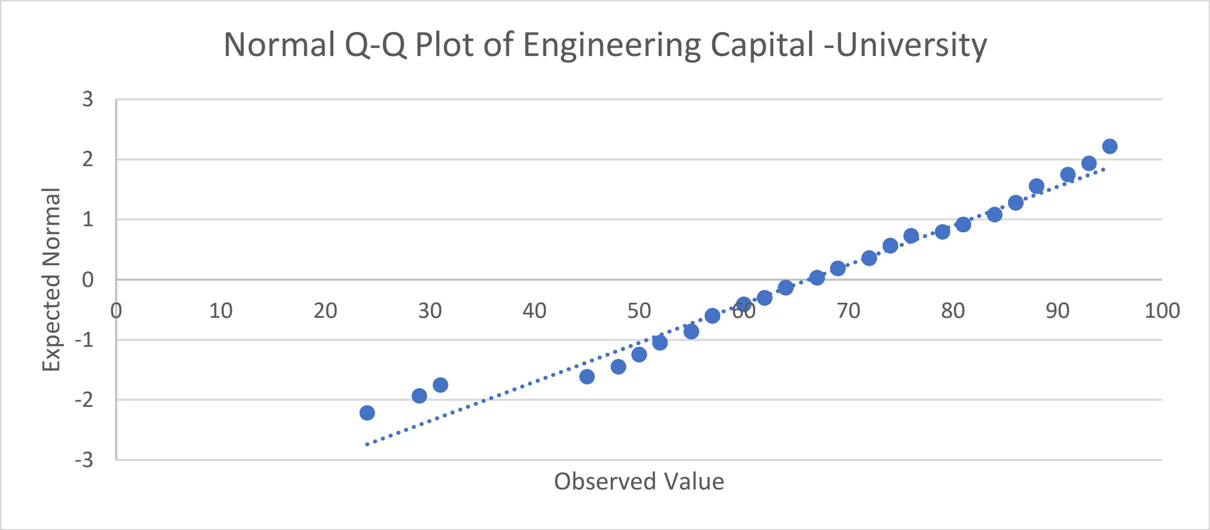
			Engineering Educational Aspiration									
			No		Unsure		Yes - FEOther		Yes – FEAca		Yes- Univer.	
			Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error
Engineering Capital Score	Mean		41.1828	.64825	45.4553	.60852	56.4835	1.24970	61.2540	1.56951	66.1892	1.68763
	95% Confidence Interval for Mean	Lower Bound	39.9069		44.2587		54.0008		58.1166		62.8258	
		Upper Bound	42.4586		46.6519		58.9663		64.3914		69.5526	
	5% Trimmed Mean		40.8161		45.2439		56.4383		61.4180		66.6952	
	Median		41.0000		45.0000		57.0000		60.0000		67.0000	
	Variance		121.866		136.640		142.119		155.193		210.758	
	Std. Deviation		11.03930		11.68931		11.92137		12.45763		14.51751	
	Minimum		17.00		17.00		26.00		36.00		24.00	
	Maximum		74.00		76.00		91.00		84.00		95.00	
	Range		57.00		59.00		65.00		48.00		71.00	
	Interquartile Range		15.00		14.00		16.00		20.00		17.50	
	Skewness		.469	.143	.232	.127	.025	.253	-.013	.302	-.382	.279
	Kurtosis		.088	.285	-.315	.253	.131	.500	-.957	.595	.424	.552

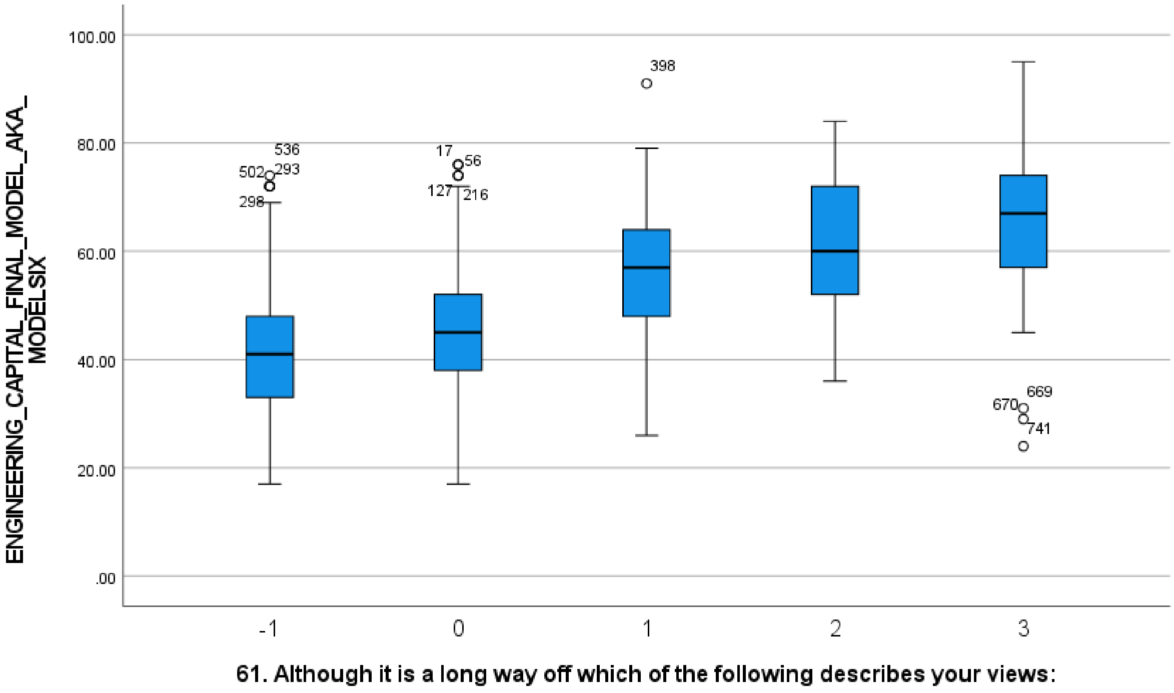

Normal Q-Q Plot of Engineering Capital Score - No
Expected Normal
Observed Value
4
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80


Normal Q-Q Plot of Engineering Capital - Unsure
Expected Normal
Observed Value
3
2
1
0
-1
-2
-3
-4
0
10
20
30
40
50
60
70
80


Normal Q-Q Plot of Engineering Capital - FE/Other
Expected Normal
Observed Value
4
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
90
100


Normal Q-Q Plot of Engineering Capital - FE/Academic
Expected Normal
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
0
10
20
30
40
50
60
70
80
90
Observed Value


Normal Q-Q Plot of Engineering Capital -University
Expected Normal
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
90
100
Observed Value


ENGINEERING_CAPITAL_FINAL_MODEL_AKA_MODELSIX
100.00
80.00
60.00
40.00
20.00
.00
536
502
293
298
17
56
127
216
398
669
670
741
-1
0
1
2
3
61. Although it is a long way off which of the following describes your views:

A one-way Welch's ANOVA was adopted to determine whether engineering capital scores differed between groups based on educational aspirations for engineering. A total of 887 participants were classified into five groups based on educational aspiration: No (N=290), Unsure (N=369), Yes-FE/Other (N=91), Yes-FE/Academic (N=63) and Yes – University (N=74). Engineering capital scores were found to statistically differ (F(4, 211.885) = 88.236, p<0.001, ETA^2=0.320). Games-Howell post-hoc testing revealed significant differences between all groups except FE-Other & FE-Academic and FE-Academic & University. The ETA^2 size of 0.320 indicates a strong effect of educational aspiration group in shaping engineering capital scores.

Descriptives

Engineering Capital Score

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
No	290	41.1828	11.03930	.64825	39.9069	42.4586	17.00	74.00
Unsure	369	45.4553	11.68931	.60852	44.2587	46.6519	17.00	76.00
FE-Other	91	56.4835	11.92137	1.24970	54.0008	58.9663	26.00	91.00
FE-Acad.	63	61.2540	12.45763	1.56951	58.1166	64.3914	36.00	84.00
Univer.	74	66.1892	14.51751	1.68763	62.8258	69.5526	24.00	95.00
Total	887	48.0417	14.30345	.48026	47.0991	48.9843	17.00	95.00

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Engineering Capital Score	Based on Mean	2.882	4	882	.022
	Based on Median	2.835	4	882	.024
	Based on Median and with adjusted df	2.835	4	855.531	.024
	Based on trimmed mean	2.872	4	882	.022

ANOVA

Engineering Capital Score

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	57964.617	4	14491.154	103.659	<.001
Within Groups	123300.839	882	139.797		
Total	181265.457	886			

ANOVA Effect Sizes[a]

			95% Confidence Interval	
		Point Estimate	Lower	Upper
Eng. Cap. Score.	Eta-squared	.320	.270	.363
	Epsilon-squared	.317	.266	.360
	Omega-squared Fixed-effect	.316	.266	.360
	Omega-squared Random-effect	.104	.083	.123

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

Robust Tests of Equality of Means

	Statistic[a]	df1	df2	Sig.
Welch	88.236	4	211.885	<.001

a. Asymptotically F distributed.

Multiple Comparisons

Engineering Capital Score

						95% Confidence Interval	
	Eng. Ed. Aspiration	Eng. Ed. Aspiration	Mean Difference (I-J)	Std. Error	Sig.	Lower Bound	Upper Bound
Games-Howell	-1	0	-4.27253*	.88912	<.001	-6.7048	-1.8402
		1	-15.30076*	1.40783	<.001	-19.1909	-11.4106
		2	-20.07121*	1.69812	<.001	-24.8049	-15.3375
		3	-25.00643*	1.80785	<.001	-30.0332	-19.9797
	0	-1	4.27253*	.88912	<.001	1.8402	6.7048
		1	-11.02823*	1.38998	<.001	-14.8712	-7.1853
		2	-15.79868*	1.68335	<.001	-20.4946	-11.1028
		3	-20.73390*	1.79399	<.001	-25.7249	-15.7429
	1	-1	15.30076*	1.40783	<.001	11.4106	19.1909
		0	11.02823*	1.38998	<.001	7.1853	14.8712
		2	-4.77045	2.00627	.128	-10.3209	.7800
		3	-9.70567*	2.09996	<.001	-15.5089	-3.9025
	2	-1	20.07121*	1.69812	<.001	15.3375	24.8049
		0	15.79868*	1.68335	<.001	11.1028	20.4946
		1	4.77045	2.00627	.128	-.7800	10.3209
		3	-4.93522	2.30466	.209	-11.3076	1.4372
	3	-1	25.00643*	1.80785	<.001	19.9797	30.0332
		0	20.73390*	1.79399	<.001	15.7429	25.7249
		1	9.70567*	2.09996	<.001	3.9025	15.5089
		2	4.93522	2.30466	.209	-1.4372	11.3076

*. The mean difference is significant at the 0.05 level.

Independent Samples T-Test: Engineering Career Aspiration (Engineer) and Engineering Capital Score

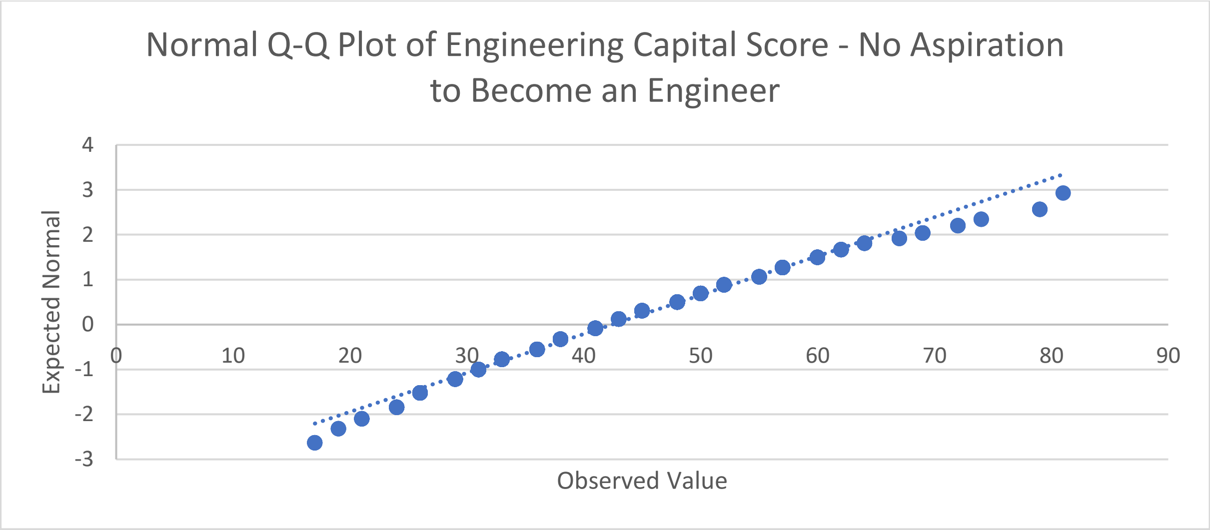
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1. The assumptions underpinning this test were met approving its use.

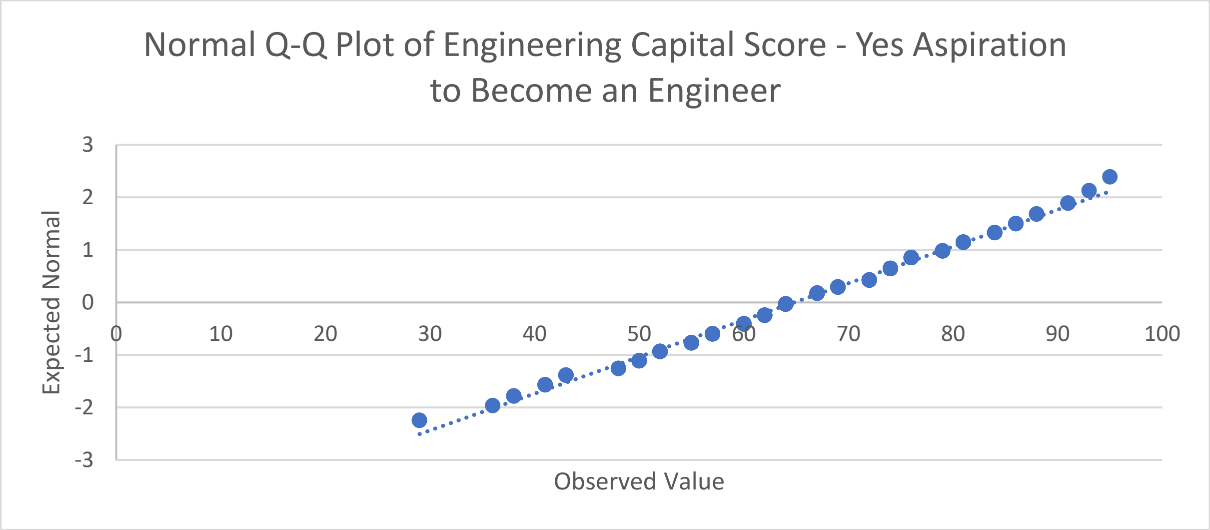
Case Processing Summary

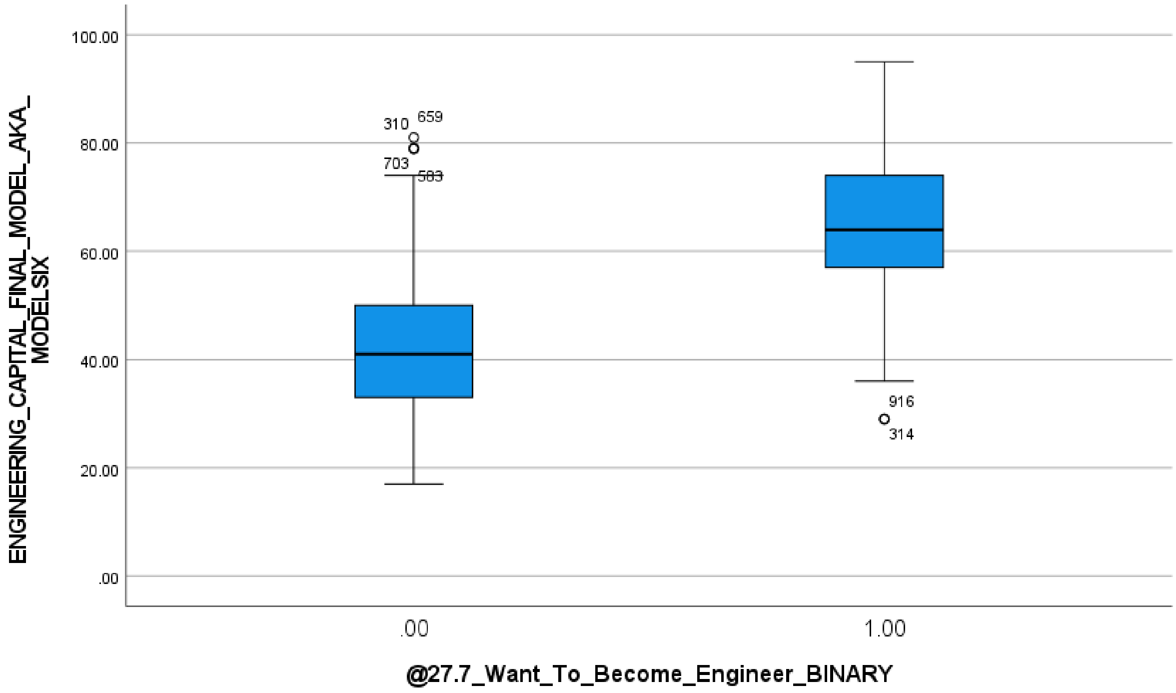
		Cases					
	I want to become an engineer	Valid		Missing		Total	
		N	Percent	N	Percent	N	Percent
Engineering Capital Score	.00	581	100.0%	0	0.0%	581	100.0%
	1.00	119	100.0%	0	0.0%	119	100.0%

Descriptives

			I want to become an engineer			
			.00		1.00	
			Statistic	Std. Error	Statistic	Std. Error
Engineering Capital Score	Mean		42.4234	.46972	64.7983	1.26136
	95% Confidence Interval for Mean	Lower Bound	41.5009		62.3005	
		Upper Bound	43.3460		67.2962	
	5% Trimmed Mean		42.1010		64.9902	
	Median		41.0000		64.0000	
	Variance		128.189		189.332	
	Std. Deviation		11.32207		13.75979	
	Minimum		17.00		29.00	
	Maximum		81.00		95.00	
	Range		64.00		66.00	
	Interquartile Range		17.00		17.00	
	Skewness		.415	.101	-.202	.222
	Kurtosis		.198	.202	-.109	.440


Normal Q-Q Plot of Engineering Capital Score - No Aspiration to Become an Engineer
Expected Normal
4
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
90
Observed Value


Normal Q-Q Plot of Engineering Capital Score - Yes Aspiration to Become an Engineer
Expected Normal
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
90
100
Observed Value


ENGINEERING_CAPITAL_FINAL_MODEL_AKA_MODELSIX
100.00
80.00
60.00
40.00
20.00
.00
310
659
703
583
916
314
.00
1.00
@27.7_Want_To_Become_Engineer_BINARY

A Welch's independent samples t-test identified a significant difference in the engineering capital scores of those who did (M=64.80, SD=13.76) and did not wish to become an engineer (M=42.42, SD=11.32) (t(152.400)=16.624, p<0.001, d=1.901). The Cohen’s d effect size highlights a strong effect of desire to become an engineer on engineering capital scores.

Group Statistics

	I want to become an engineer	N	Mean	Std. Deviation	Std. Error Mean
Engineering Capital Score	.00	581	42.4234	11.32207	.46972
	1.00	119	64.7983	13.75979	1.26136

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Engineering Capital Score	Equal variances assumed	6.818	.009	-18.893	698	.000	.000	-22.37491	1.18428	-24.70008	-20.04974
	Equal variances not assumed			-16.624	152.400	.000	.000	-22.37491	1.34598	-25.03410	-19.71572

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
Engineering Capital Score	Cohen's d	11.76970	-1.901	-2.121	-1.680
	Hedges' correction	11.78236	-1.899	-2.119	-1.678
	Glass's delta	13.75979	-1.626	-1.910	-1.338

a. The denominator used in estimating the effect sizes.

Cohen's d uses the pooled standard deviation.

Hedges' correction uses the pooled standard deviation, plus a correction factor.

Glass's delta uses the sample standard deviation of the control group.

Independent Samples T-Test: Engineering Career Aspiration (Engineer-Related Role) and Engineering Capital Score

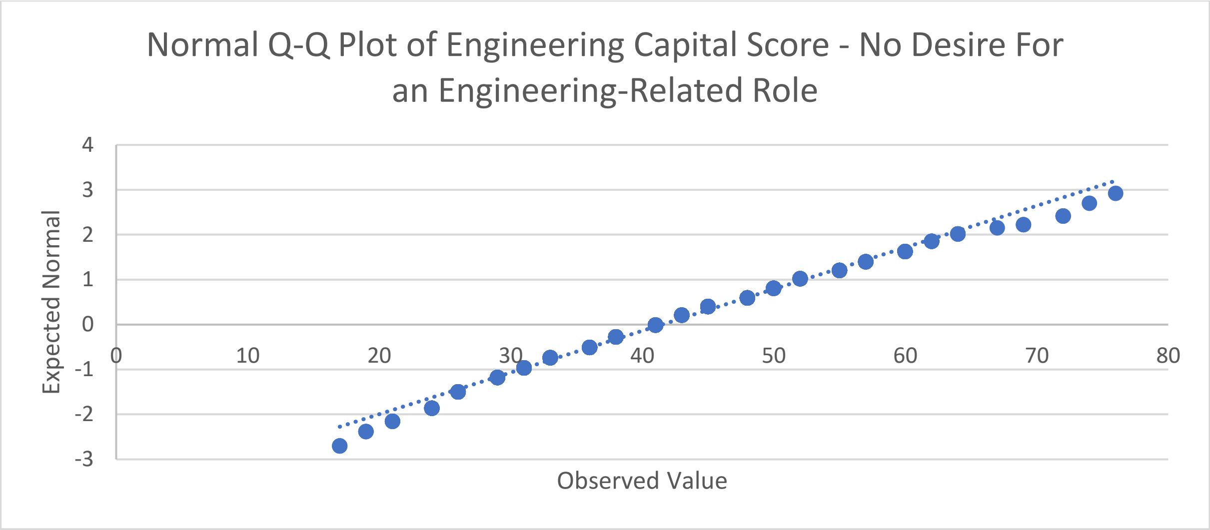
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1. The assumptions underpinning this test were met approving its use.

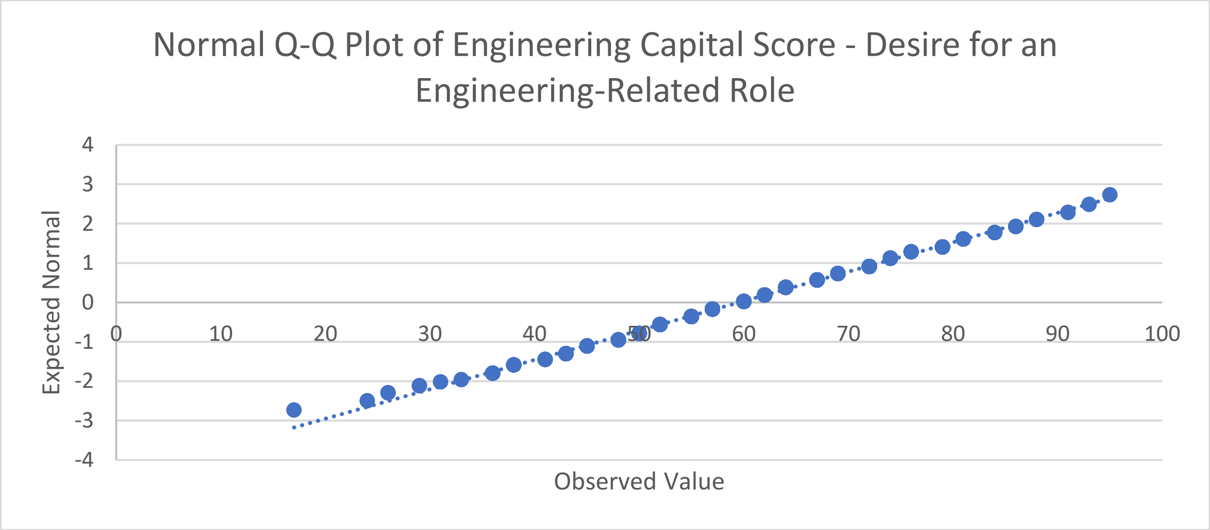
Case Processing Summary

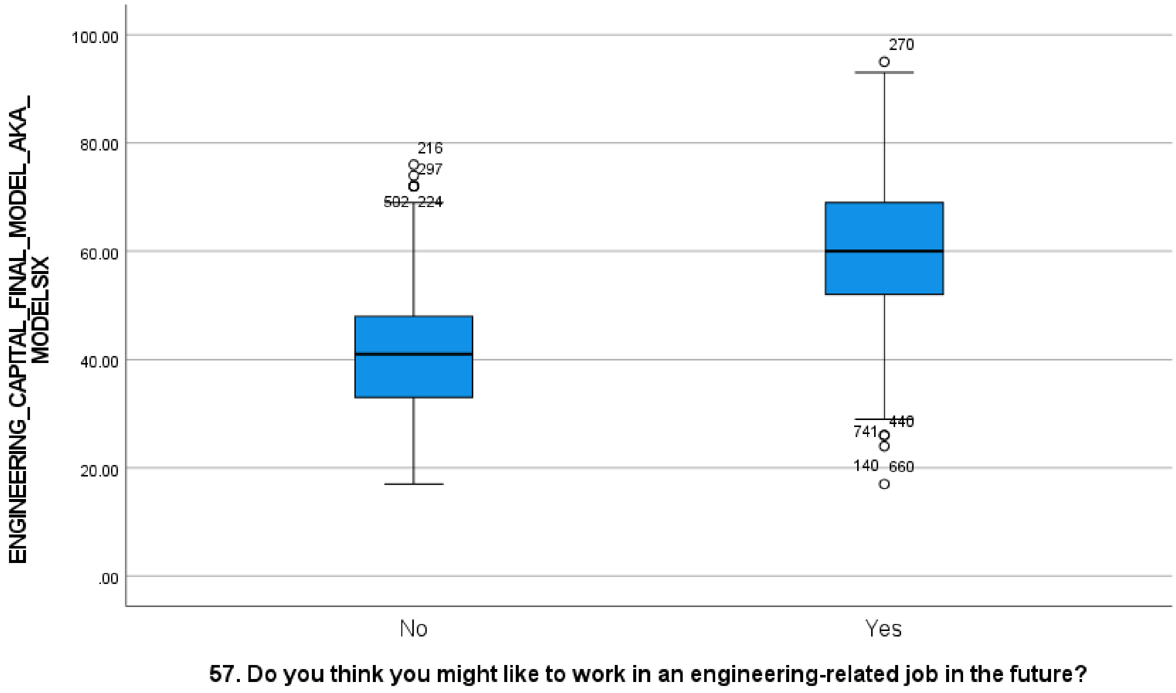
		Cases					
	Desire an engineering role	Valid		Missing		Total	
		N	Percent	N	Percent	N	Percent
Engineering Capital Score	No	576	100.0%	0	0.0%	576	100.0%
	Yes	316	100.0%	0	0.0%	316	100.0%

Descriptives

			Desire an engineering role			
			No		Yes	
			Statistic	Std. Error	Statistic	Std. Error
Engineering Capital Score	Mean		41.5087	.44093	59.5380	.73969
	95% Confidence Interval for Mean	Lower Bound	40.6426		58.0826	
		Upper Bound	42.3747		60.9933	
	5% Trimmed Mean		41.2658		59.5844	
	Median		41.0000		60.0000	
	Variance		111.986		172.897	
	Std. Deviation		10.58234		13.14903	
	Minimum		17.00		17.00	
	Maximum		76.00		95.00	
	Range		59.00		78.00	
	Interquartile Range		15.00		17.00	
	Skewness		.333	.102	-.055	.137
	Kurtosis		-.026	.203	.152	.273


Normal Q-Q Plot of Engineering Capital Score - No Desire For an Engineering-Related Role


Normal Q-Q Plot of Engineering Capital Score - Desire for an Engineering-Related Role



A Welch's independent samples t-test identified a significant difference in the engineering capital scores of those who did (M=59.54, SD=13.15) and did not wish to work in an engineering-related role (M=41.51, SD=10.58) (t(541.201)=20.937, p<0.001, d=1.560). The Cohen's d effect size highlights a strong effect of desire to work in an engineering role on engineering capital scores.

Group Statistics

	Desire for an engineering-related job in the future?	N	Mean	Std. Deviation	Std. Error Mean
Engineering Capital Score	No	576	41.5087	10.58234	.44093
	Yes	316	59.5380	13.14903	.73969

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Engineering Capital	Equal variances assumed	15.690	.000	-22.286	890	.000	.000	-18.02929	.80898	-19.61703	-16.44155
	Equal variances not assumed			-20.937	541.201	.000	.000	-18.02929	.86114	-19.72088	-16.33771

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
Engineering Capital Score	Cohen's d	11.55614	-1.560	-1.715	-1.405
	Hedges' correction	11.56589	-1.559	-1.714	-1.403
	Glass's delta	13.14903	-1.371	-1.544	-1.196

a. The denominator used in estimating the effect sizes.

Cohen's d uses the pooled standard deviation.

Hedges' correction uses the pooled standard deviation, plus a correction factor.

Glass's delta uses the sample standard deviation of the control group.

Independent Samples T-Test: Gender and Engineering Capital Score

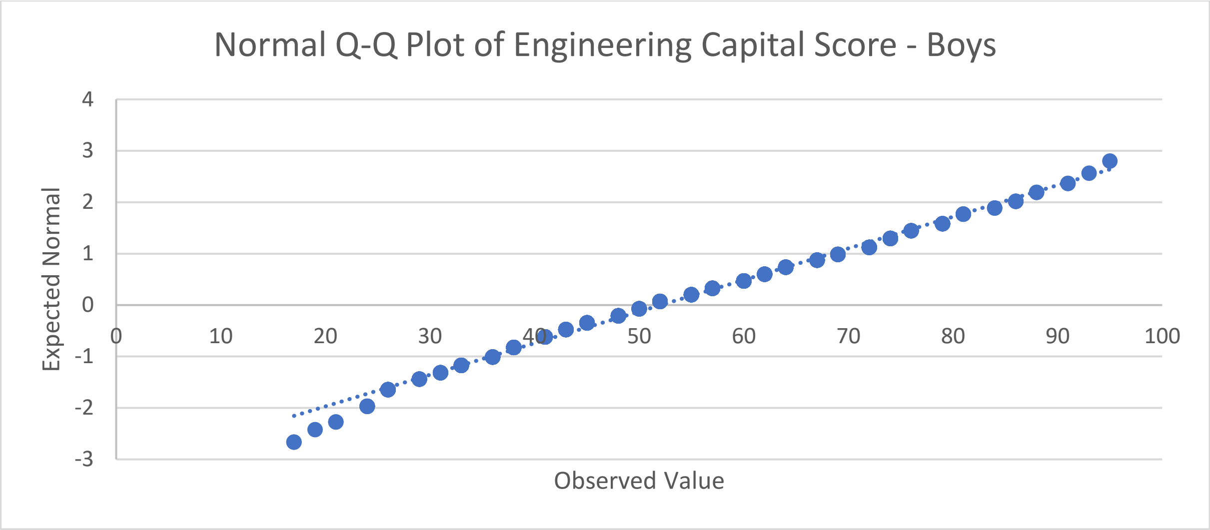
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1. The assumptions underpinning this test were met approving its use.

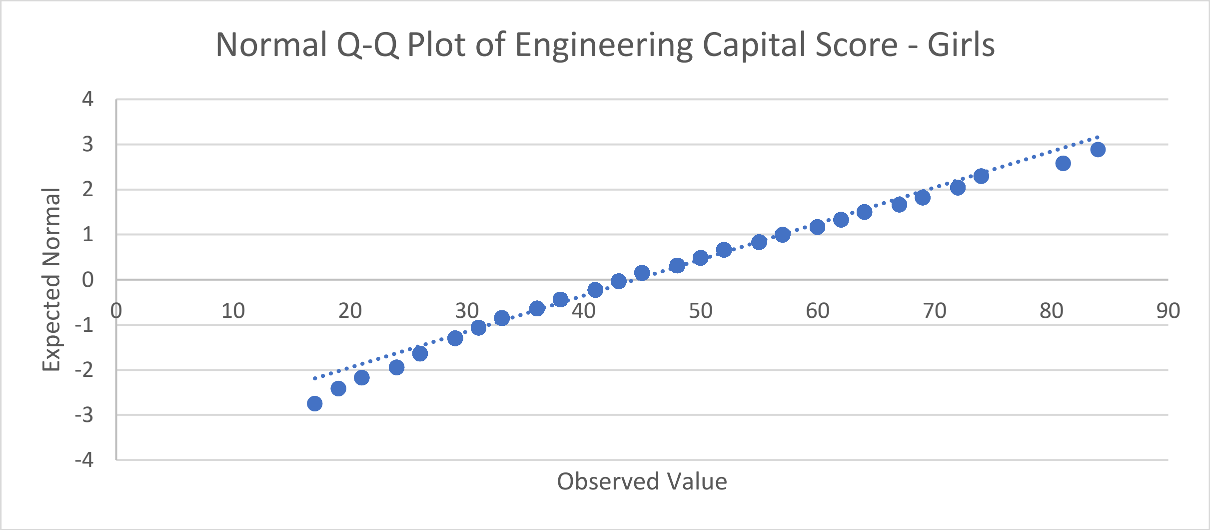
Case Processing Summary

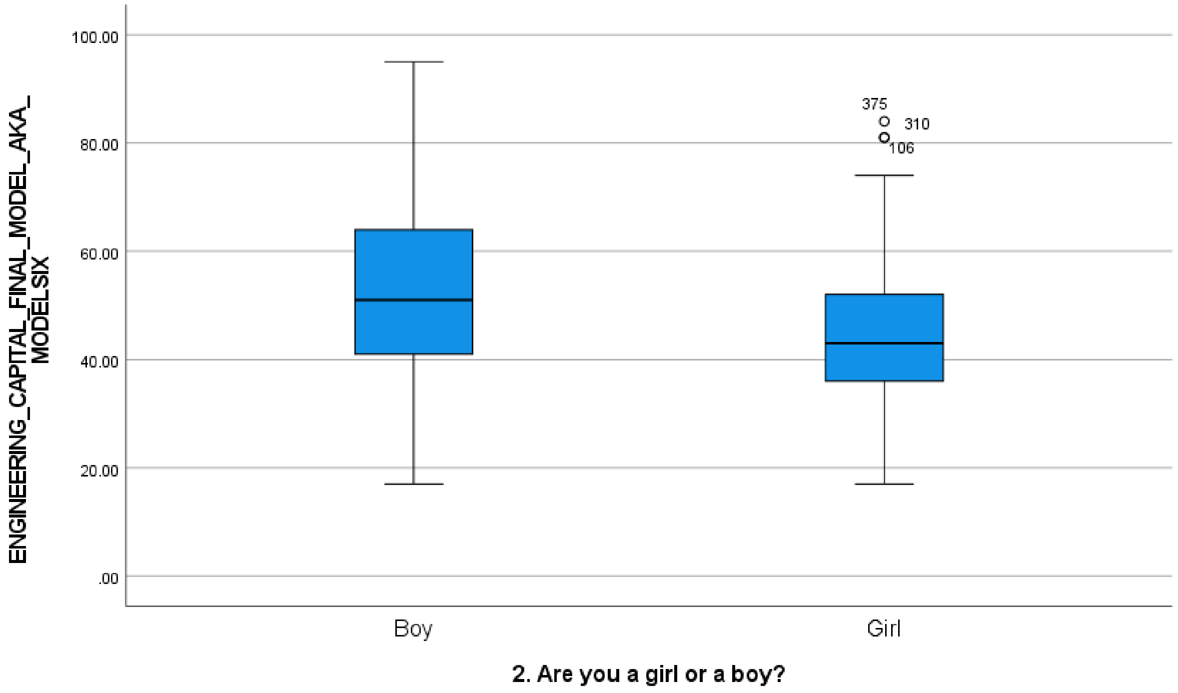
		Cases					
	2. Are you a girl or a boy?	Valid		Missing		Total	
		N	Percent	N	Percent	N	Percent
Engineering Capital Score	Boy	388	100.0%	0	0.0%	388	100.0%
	Girl	505	100.0%	0	0.0%	505	100.0%

Descriptives

			2. Are you a girl or a boy?			
			Boy		Girl	
			Statistic	Std. Error	Statistic	Std. Error
Engineering Capital Score	Mean		52.0722	.81114	44.4277	.54646
	95% Confidence Interval for Mean	Lower Bound	50.4774		43.3541	
		Upper Bound	53.6670		45.5013	
	5% Trimmed Mean		51.8270		44.0963	
	Median		51.0000		43.0000	
	Variance		255.282		150.801	
	Std. Deviation		15.97753		12.28010	
	Minimum		17.00		17.00	
	Maximum		95.00		84.00	
	Range		78.00		67.00	
	Interquartile Range		23.00		16.00	
	Skewness		.213	.124	.371	.109
	Kurtosis		-.492	.247	-.190	.217


Normal Q-Q Plot of Engineering Capital Score - Boys
Expected Normal
4
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
90
100
Observed Value


Normal Q-Q Plot of Engineering Capital Score - Girls
Expected Normal
4
3
2
1
0
-1
-2
-3
-4
0
10
20
30
40
50
60
70
80
90
Observed Value


ENGINEERING_CAPITAL_FINAL_MODEL_AKA_MODELSIX
100.00
80.00
60.00
40.00
20.00
.00
375
310
106
Boy
Girl
2. Are you a girl or a boy?

A Welch's independent samples t-test identified a significant difference in the engineering capital scores of girls (N=505, M=44.43, SD=12.28) and boys (N=388, M=52.07, SD=15.98) (t(706.293)=7.816, p<0.001, d=0.546). The Cohen's d effect size highlights a medium effect of gender on engineering capital scores.

Group Statistics

	2. Are you a girl or a boy?	N	Mean	Std. Deviation	Std. Error Mean
Engineering Capital Score	Boy	388	52.0722	15.97753	.81114
	Girl	505	44.4277	12.28010	.54646

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Eng. Cap. Score	Equal variances assumed	32.804	.000	8.084	891	.000	.000	7.64444	.94557	5.78864	9.50024
	Equal variances not assumed			7.816	706.293	.000	.000	7.64444	.97804	5.72423	9.56465

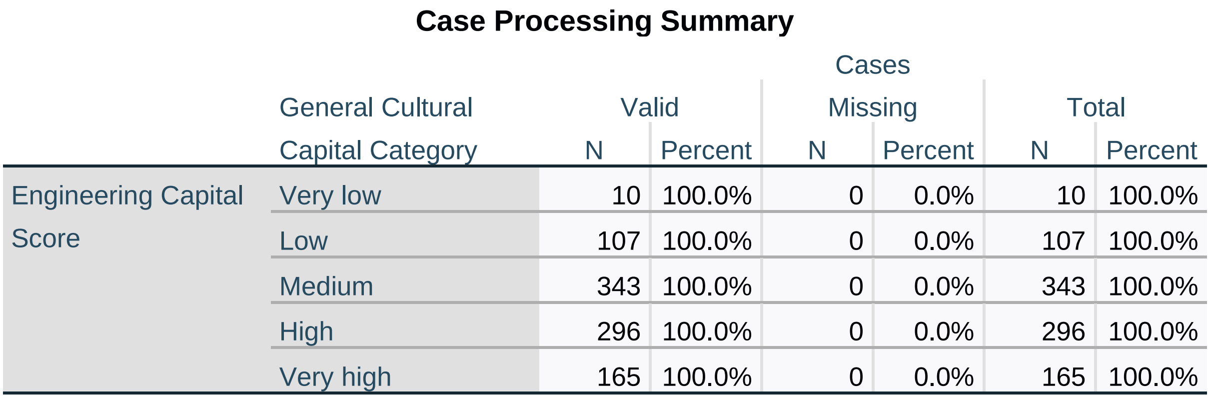
Independent Samples Effect Sizes

		Standardizer^a	Point Estimate	95% Confidence Interval	
				Lower	Upper
Engineering Capital Score	Cohen's d	14.00648	.546	.411	.680
	Hedges' correction	14.01828	.545	.411	.680
	Glass's delta	12.28010	.623	.484	.760

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

One-Way ANOVA: Deprivation (Cultural Capital) and Engineering Capital Score

An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1. The assumptions underpinning this test were met approving its use.

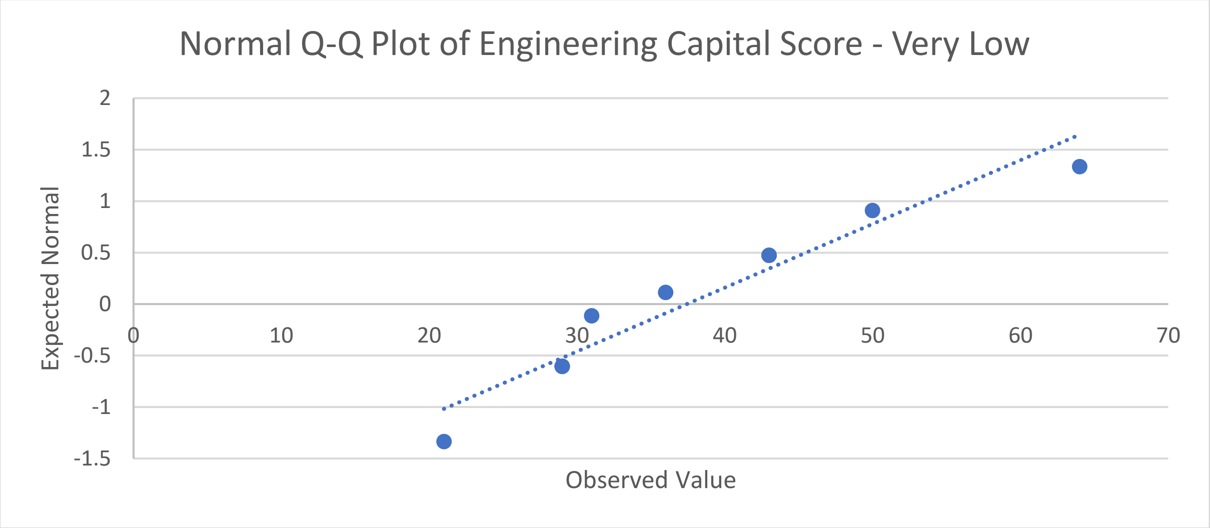


Case Processing Summary

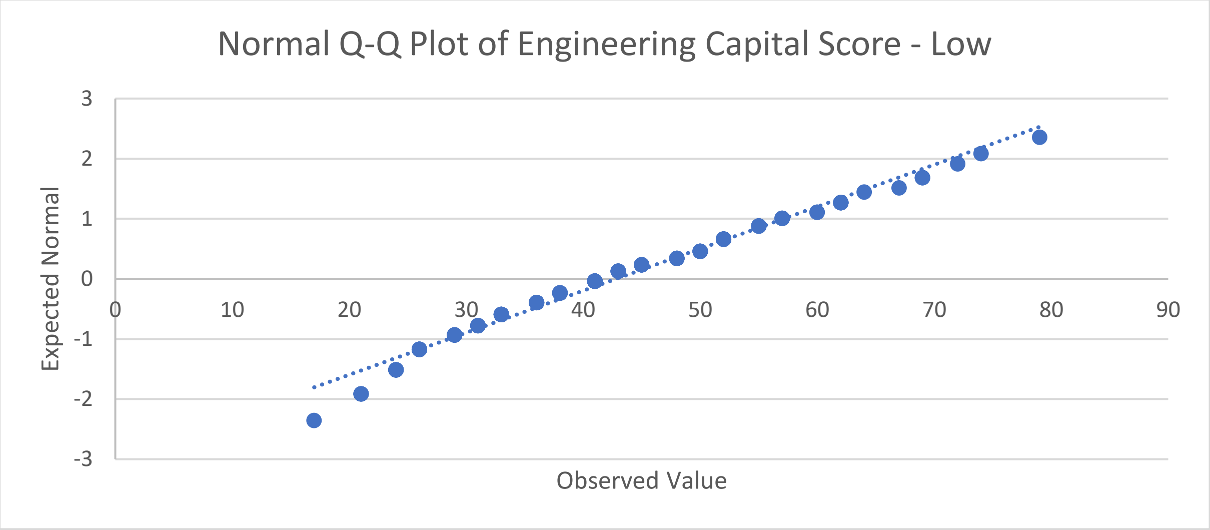
		Cases					
	General Cultural Capital Category	Valid		Missing		Total	
		N	Percent	N	Percent	N	Percent
Engineering Capital Score	Very low	10	100.0%	0	0.0%	10	100.0%
	Low	107	100.0%	0	0.0%	107	100.0%
	Medium	343	100.0%	0	0.0%	343	100.0%
	High	296	100.0%	0	0.0%	296	100.0%
	Very high	165	100.0%	0	0.0%	165	100.0%

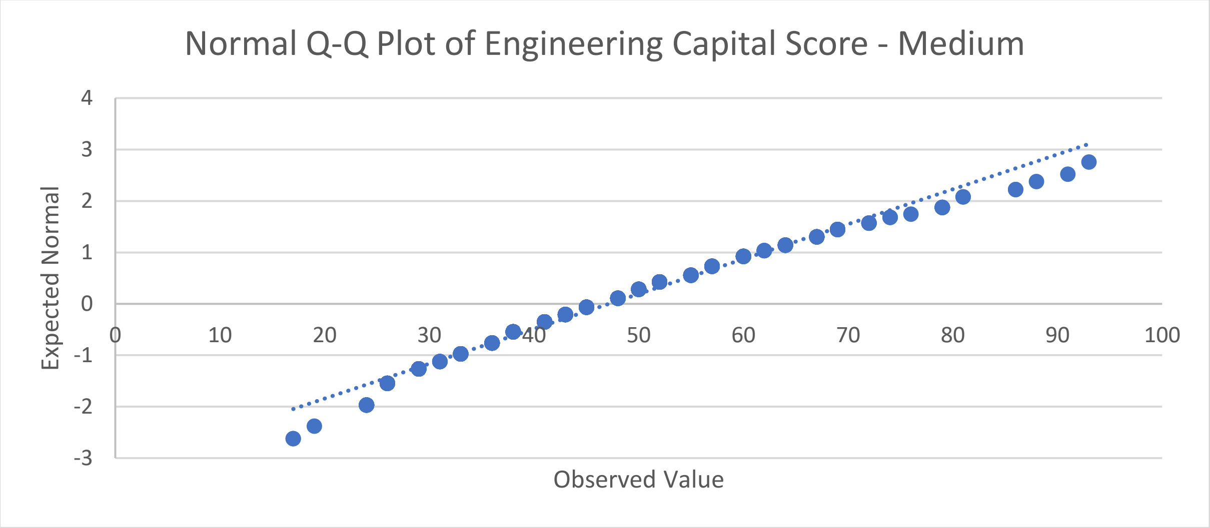
Descriptives

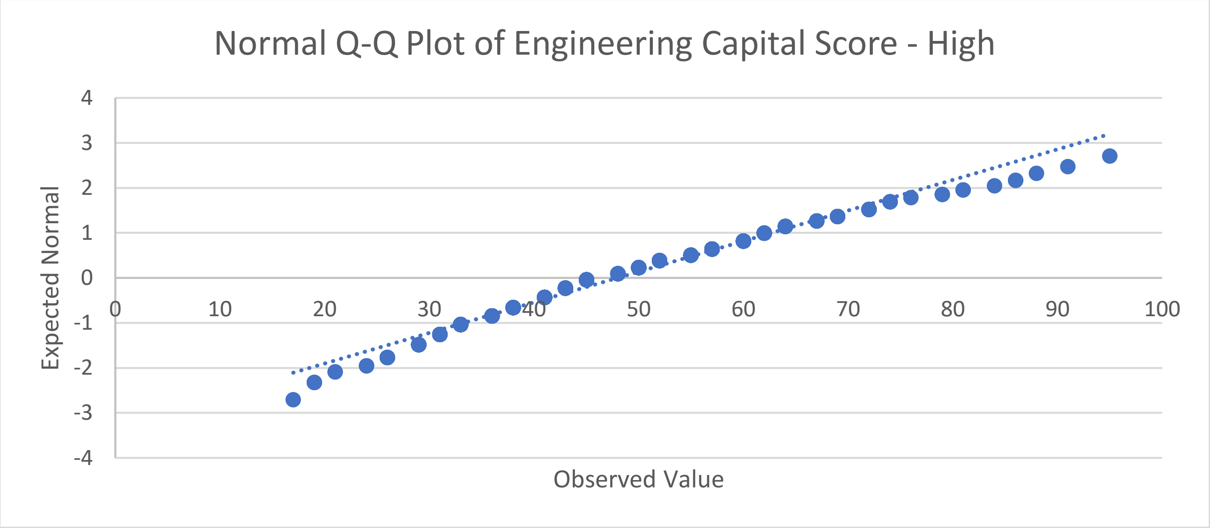
			General Cultural Capital Category									
			Very low		Low		Medium		High		Very high	
			Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error
Eng. Cap. Score	Mean		37.5000	4.01732	42.8318	1.32069	47.1778	.77552	48.0000	.83199	51.8848	1.09475
	95% Confidence Interval for Mean	Lower Bound	28.4122		40.2134		45.6524		46.3626		49.7232	
		Upper Bound	46.5878		45.4502		48.7032		49.6374		54.0465	
	5% Trimmed Mean		36.9444		42.4034		46.6223		47.5135		51.6077	
	Median		33.5000		41.0000		45.0000		45.0000		50.0000	
	Variance		161.389		186.632		206.293		204.895		197.749	
	Std. Deviation		12.70389		13.66133		14.36290		14.31415		14.06232	
	Minimum		21.00		17.00		17.00		17.00		26.00	
	Maximum		64.00		79.00		93.00		95.00		84.00	
	Range		43.00		62.00		76.00		78.00		58.00	
	Interquartile Range		15.75		19.00		21.00		19.00		21.00	
	Skewness		.968	.687	.394	.234	.496	.132	.522	.142	.329	.189
	Kurtosis		.780	1.334	-.464	.463	.072	.263	.170	.282	-.764	.376

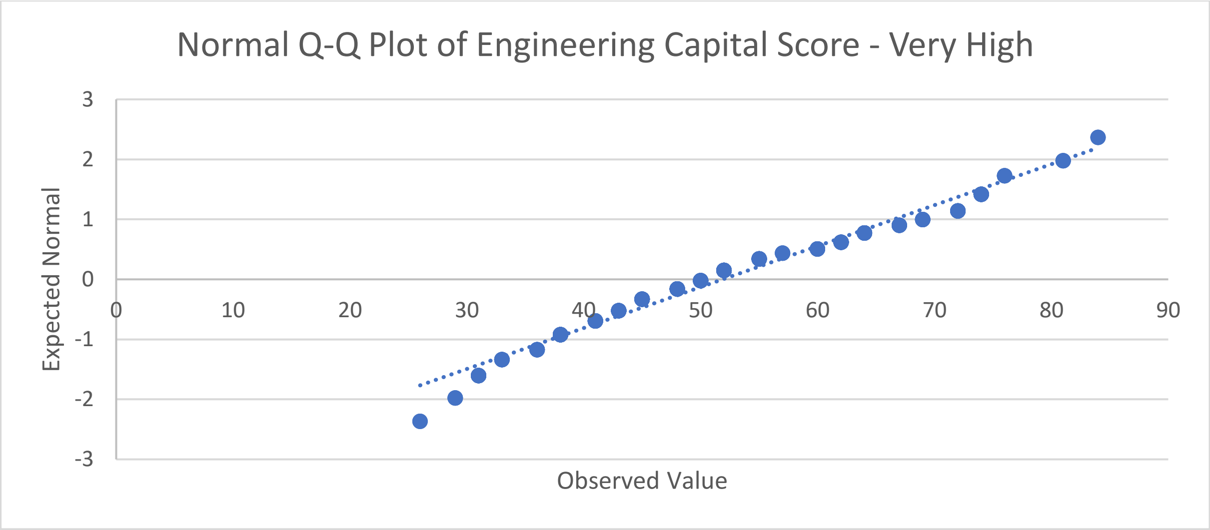


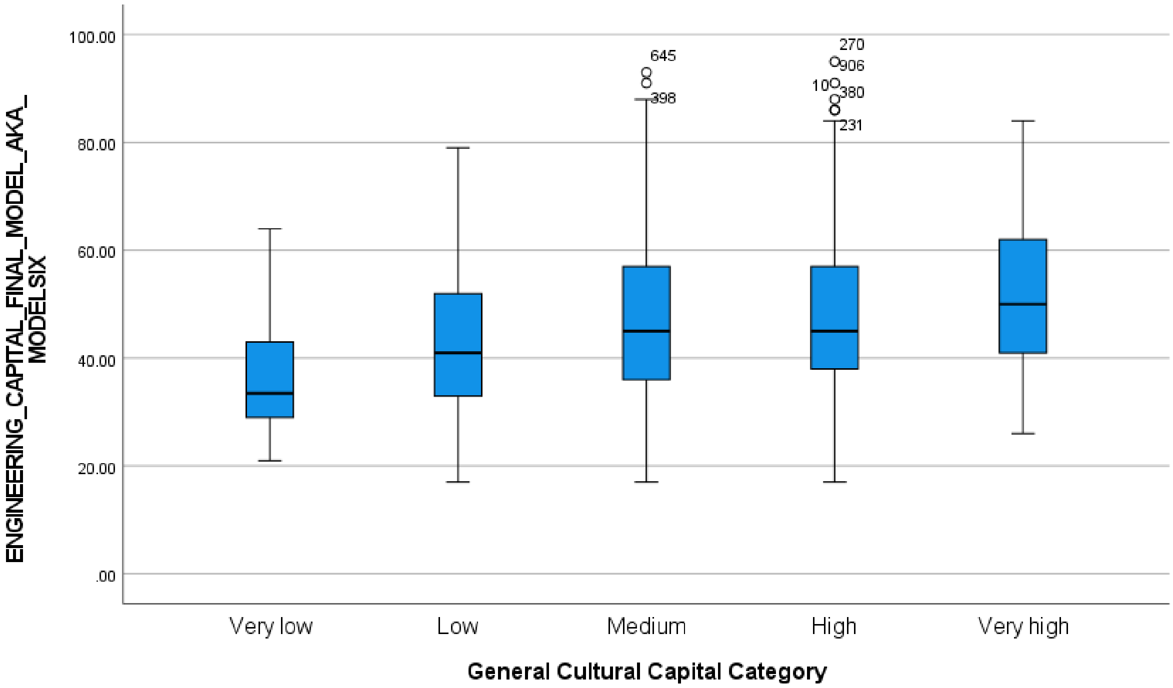
Normal Q-Q Plot of Engineering Capital Score - Very Low


Normal Q-Q Plot of Engineering Capital Score - Low
Expected Normal
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
90
Observed Value


Normal Q-Q Plot of Engineering Capital Score - Medium
Expected Normal
4
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
90
100
Observed Value


Normal Q-Q Plot of Engineering Capital Score - High
Expected Normal
4
3
2
1
0
-1
-2
-3
-4
0
10
20
30
40
50
60
70
80
90
100
Observed Value


Normal Q-Q Plot of Engineering Capital Score - Very High
Expected Normal
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
90
Observed Value


ENGINEERING_CAPITAL_FINAL_MODEL_AKA_MODELSIX
100.00
80.00
60.00
40.00
20.00
.00
645
398
270
906
100
380
231
Very low
Low
Medium
High
Very high
General Cultural Capital Category

A one-way ANOVA was adopted to determine whether engineering capital scores differed between groups based on deprivation measured through cultural capital scores. A total of 921 participants were classified into five groups based on general cultural capital scores: Very Low (N=10), Low (N=107), Medium (N=343), High (N=296) and Very High (N=165). Engineering capital scores were found to statistically differ (F(4, 916) = 8.167, p<0.001, ETA^2=0.034). Tukey post-hoc testing revealed significant differences between all groups except Very Low & Low, Very Low & Medium, Very Low and High and Medium and High. The ETA^2 size of 0.034 indicates a small effect of general cultural capital group in shaping engineering capital scores.

Descriptives

Engineering Capital Score

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum	Between-Component Variance
						Lower Bound	Upper Bound			
Very low		10	37.5000	12.70389	4.01732	28.4122	46.5878	21.00	64.00	
Low		107	42.8318	13.66133	1.32069	40.2134	45.4502	17.00	79.00	
Medium		343	47.1778	14.36290	.77552	45.6524	48.7032	17.00	93.00	
High		296	48.0000	14.31415	.83199	46.3626	49.6374	17.00	95.00	
Very high		165	51.8848	14.06232	1.09475	49.7232	54.0465	26.00	84.00	
Total		921	47.6754	14.41798	.47509	46.7430	48.6077	17.00	95.00	
Model	Fixed Effects			14.19847	.46786	46.7572	48.5935			
	Random Effects				1.65931	43.0684	52.2823			8.80924

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Eng. Cap. Score	Based on Mean	.107	4	916	.980
	Based on Median	.136	4	916	.969
	Based on Median and with adjusted df	.136	4	908.225	.969
	Based on trimmed mean	.120	4	916	.975

ANOVA

Eng. Cap. Score.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	6585.495	4	1646.374	8.167	.000
Within Groups	184662.436	916	201.597		
Total	191247.931	920			

ANOVA Effect Sizes[a]

		Point Estimate	95% Confidence Interval	
			Lower	Upper
Eng. Cap. Score.	Eta-squared	.034	.012	.057
	Epsilon-squared	.030	.008	.053
	Omega-squared Fixed-effect	.030	.008	.053
	Omega-squared Random-effect	.008	.002	.014

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

Multiple Comparisons

Eng. Cap. Score.

	(I) General Cultural Capital Category	(J) General Cultural Capital Category	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Tukey HSD	Very low	Low	-5.33178	4.69508	.788	-18.1644	7.5009
		Medium	-9.67784	4.55493	.210	-22.1275	2.7718
		High	-10.50000	4.56516	.146	-22.9776	1.9776
		Very high	-14.38485*	4.62401	.016	-27.0233	-1.7464
	Low	Very low	5.33178	4.69508	.788	-7.5009	18.1644
		Medium	-4.34607*	1.57220	.046	-8.6432	-.0489
		High	-5.16822*	1.60161	.011	-9.5458	-.7907
		Very high	-9.05307*	1.76235	.000	-13.8700	-4.2362
	Medium	Very low	9.67784	4.55493	.210	-2.7718	22.1275
		Low	4.34607*	1.57220	.046	.0489	8.6432
		High	-.82216	1.12642	.950	-3.9009	2.2566
		Very high	-4.70701*	1.34519	.004	-8.3837	-1.0303
	High	Very low	10.50000	4.56516	.146	-1.9776	22.9776
		Low	5.16822*	1.60161	.011	.7907	9.5458
		Medium	.82216	1.12642	.950	-2.2566	3.9009
		Very high	-3.88485*	1.37944	.040	-7.6552	-.1145
	Very high	Very low	14.38485*	4.62401	.016	1.7464	27.0233
		Low	9.05307*	1.76235	.000	4.2362	13.8700
		Medium	4.70701*	1.34519	.004	1.0303	8.3837
		High	3.88485*	1.37944	.040	.1145	7.6552

*. The mean difference is significant at the 0.05 level.

One-Way ANOVA: Deprivation (IDACI) and Engineering Capital Score

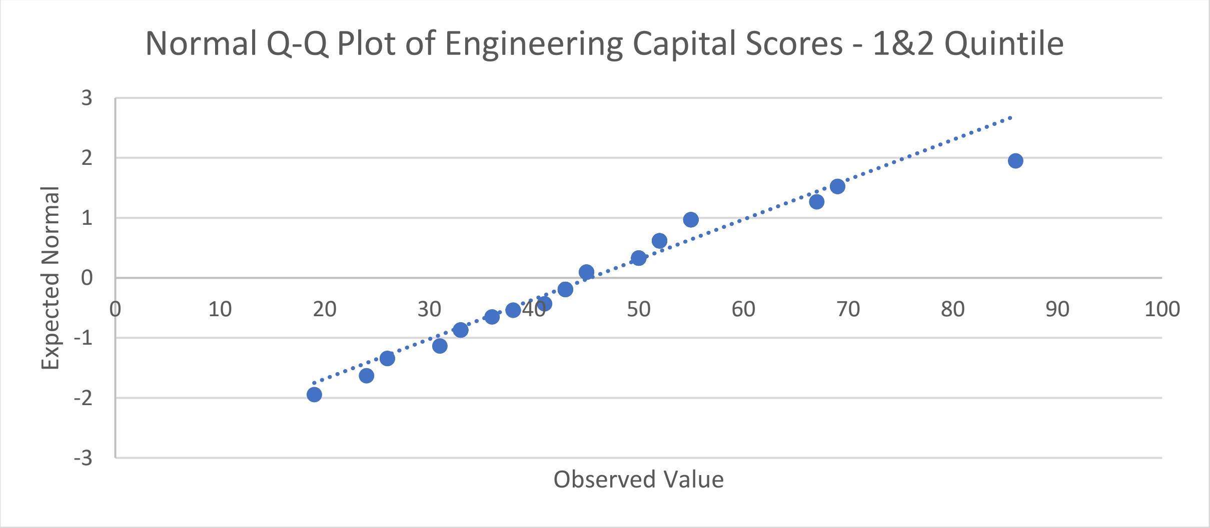
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1 – the 1&2 group did express a slight degree of kurtosis however this was deemed as acceptable given its scale and the robustness of the ANOVA procedure. The assumptions underpinning this test were met approving its use.

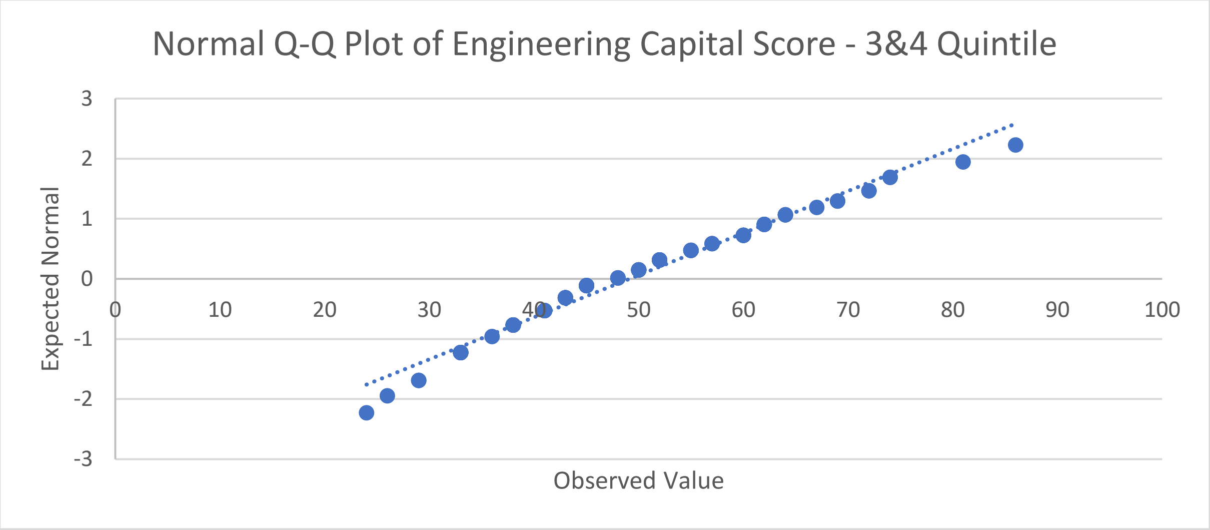
Case Processing Summary

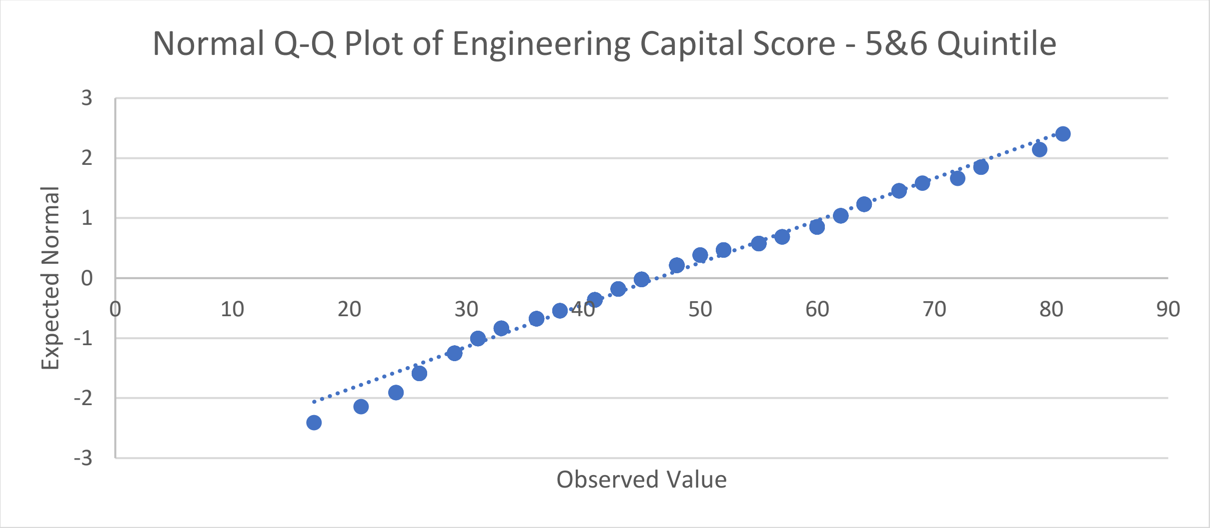
		Cases					
	IDACI	Valid		Missing		Total	
	Decile	N	Percent	N	Percent	N	Percent
Eng. Cap. Score	12	38	100.0%	0	0.0%	38	100.0%
	34	76	100.0%	0	0.0%	76	100.0%
	56	123	100.0%	0	0.0%	123	100.0%
	78	219	100.0%	0	0.0%	219	100.0%
	910	150	100.0%	0	0.0%	150	100.0%

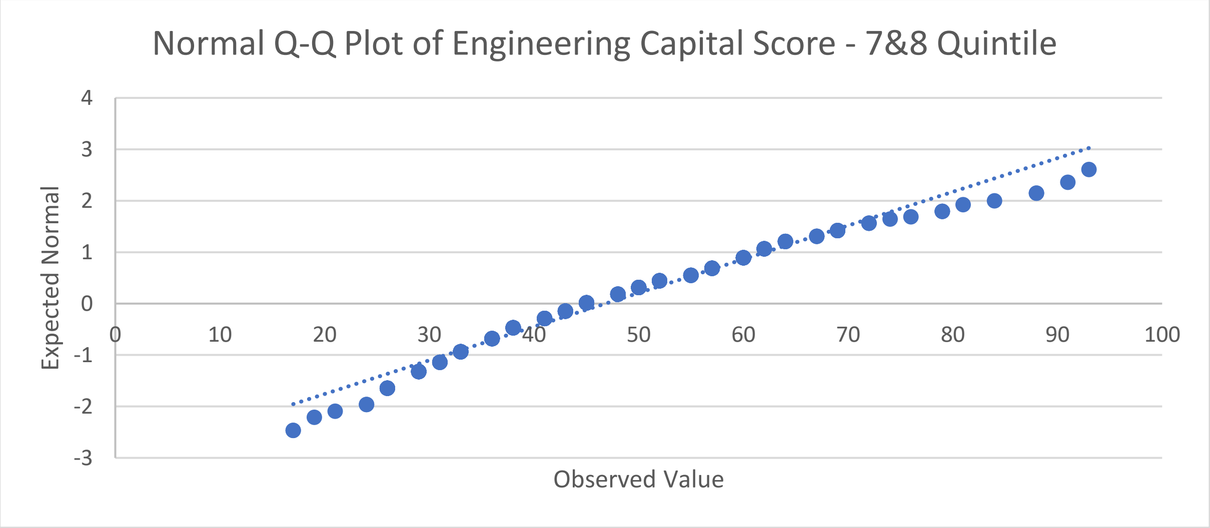
Descriptives

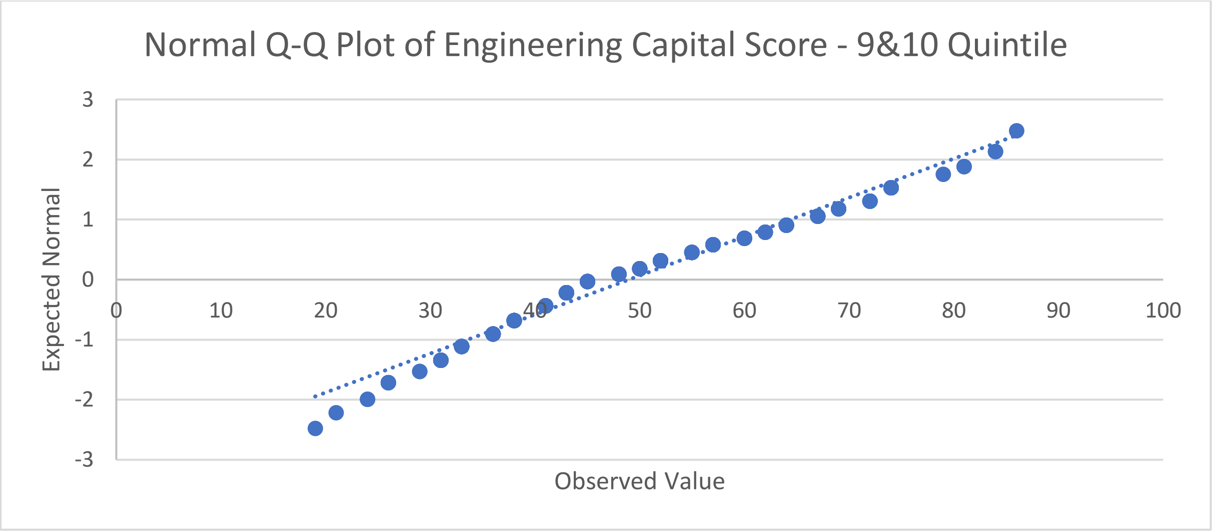
			IDACI Decile									
			12		34		56		78		910	
			Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error
Eng. Cap. Score	Mean		45.3421	2.20541	49.1447	1.54496	46.3333	1.23332	46.8447	.99505	48.9733	1.20821
	95% Confidence Interval for Mean	Lower Bound	40.8735		46.0670		43.8919		44.8836		46.5859	
		Upper Bound	49.8107		52.2225		48.7748		48.8059		51.3608	
	5% Trimmed Mean		44.8626		48.7222		46.0050		46.1695		48.6000	
	Median		44.0000		48.0000		45.0000		45.0000		45.0000	
	Variance		184.826		181.405		187.093		216.838		218.966	
	Std. Deviation		13.59506		13.46868		13.67819		14.72543		14.79749	
	Minimum		19.00		24.00		17.00		17.00		19.00	
	Maximum		86.00		86.00		81.00		93.00		86.00	
	Range		67.00		62.00		64.00		76.00		67.00	
	Interquartile Range		16.75		22.00		21.00		21.00		22.00	
	Skewness		.617	.383	.492	.276	.278	.218	.628	.164	.453	.198
	Kurtosis		1.153	.750	-.211	.545	-.490	.433	.290	.327	-.437	.394

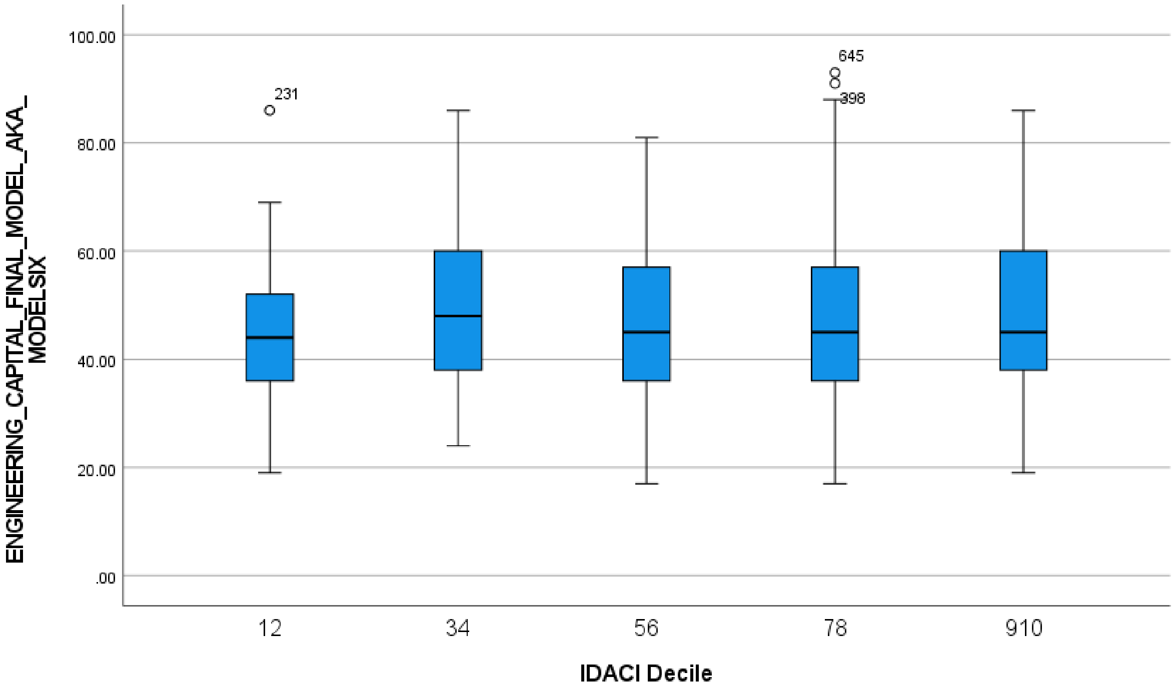

Normal Q-Q Plot of Engineering Capital Scores - 1&2 Quintile


Normal Q-Q Plot of Engineering Capital Score - 3&4 Quintile
Expected Normal
Observed Value
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
90
100


Normal Q-Q Plot of Engineering Capital Score - 5&6 Quintile
Expected Normal
Observed Value
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
90


Normal Q-Q Plot of Engineering Capital Score - 7&8 Quintile
Expected Normal
Observed Value
4
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
90
100


Normal Q-Q Plot of Engineering Capital Score - 9&10 Quintile
Expected Normal
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
90
100
Observed Value


ENGINEERING_CAPITAL_FINAL_MODEL_AKA_MODELSIX
100.00
80.00
60.00
40.00
20.00
.00
231
645
398
12
34
56
78
910
IDACI Decile

A one-way ANOVA was adopted to determine whether engineering capital scores differed between groups based on deprivation measured by the IDACI index. A total of 606 participants were classified into five groups based on IDACI quintile: 1&2 (N=38), 3&4 (N=76), 5&6 (N=123), 7&8 (N=219) and 9&10 (N=150). Engineering capital scores were not found to statistically differ (F(4, 601) = 1.182, p=0.318, ETA^2=0.008).

Descriptives

Eng. Cap. Score.

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum	Between-Component Variance
12		38	45.3421	13.59506	2.20541	40.8735	49.8107	19.00	86.00	
34		76	49.1447	13.46868	1.54496	46.0670	52.2225	24.00	86.00	
56		123	46.3333	13.67819	1.23332	43.8919	48.7748	17.00	81.00	
78		219	46.8447	14.72543	.99505	44.8836	48.8059	17.00	93.00	
910		150	48.9733	14.79749	1.20821	46.5859	51.3608	19.00	86.00	
Total		606	47.4620	14.32415	.58188	46.3193	48.6048	17.00	93.00	
Model	Fixed Effects			14.31555	.58153	46.3200	48.6041			
	Random Effects				.64909	45.6599	49.2642			.32898

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Eng. Cap. Score.	Based on Mean	.711	4	601	.585
	Based on Median	.505	4	601	.732
	Based on Median and with adjusted df	.505	4	590.872	.732
	Based on trimmed mean	.682	4	601	.604

ANOVA

Eng. Cap. Score.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	968.718	4	242.180	1.182	.318
Within Groups	123165.909	601	204.935		
Total	124134.627	605			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval	
			Lower	Upper
Eng. Cap. Score.	Eta-squared	.008	.000	.021
	Epsilon-squared	.001	-.007	.014
	Omega-squared Fixed-effect	.001	-.007	.014
	Omega-squared Random-effect	.000	-.002	.004

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.

One-Way ANOVA: Science Academic Ability and Engineering Capital Score

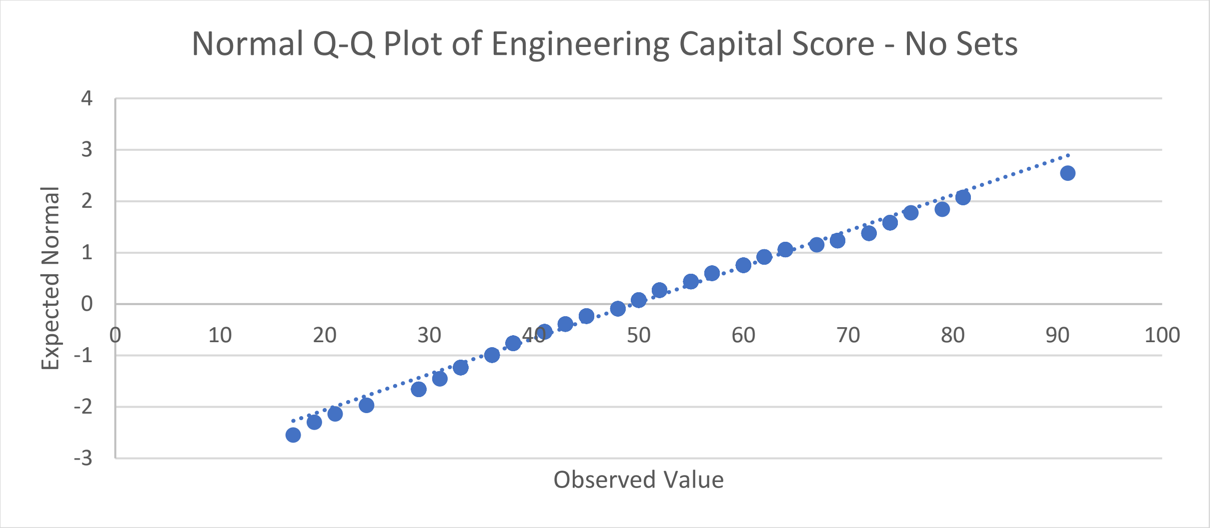
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1. The assumptions underpinning this test were met approving its use.

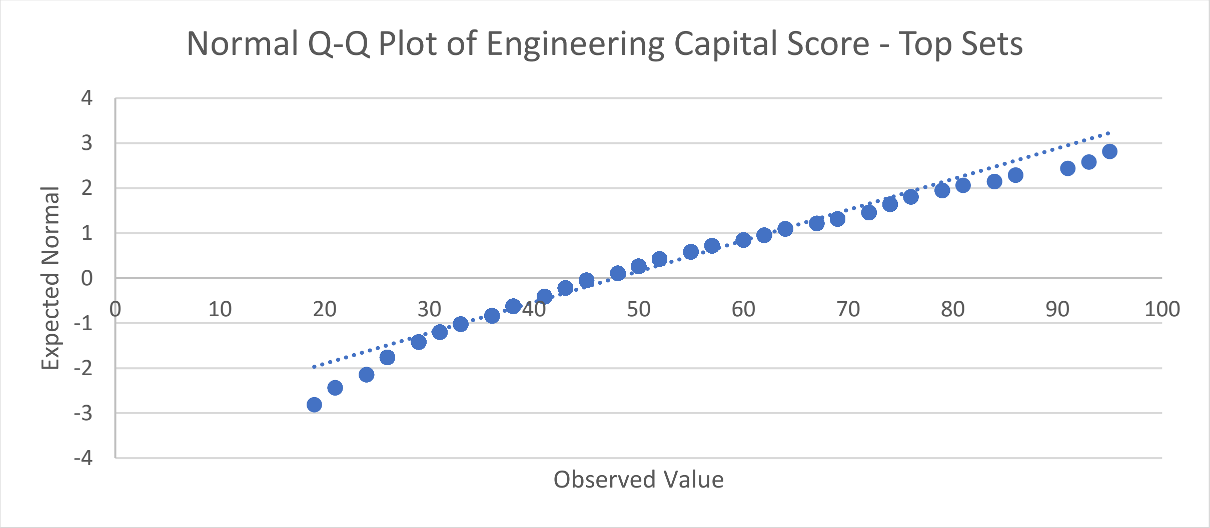
Case Processing Summary

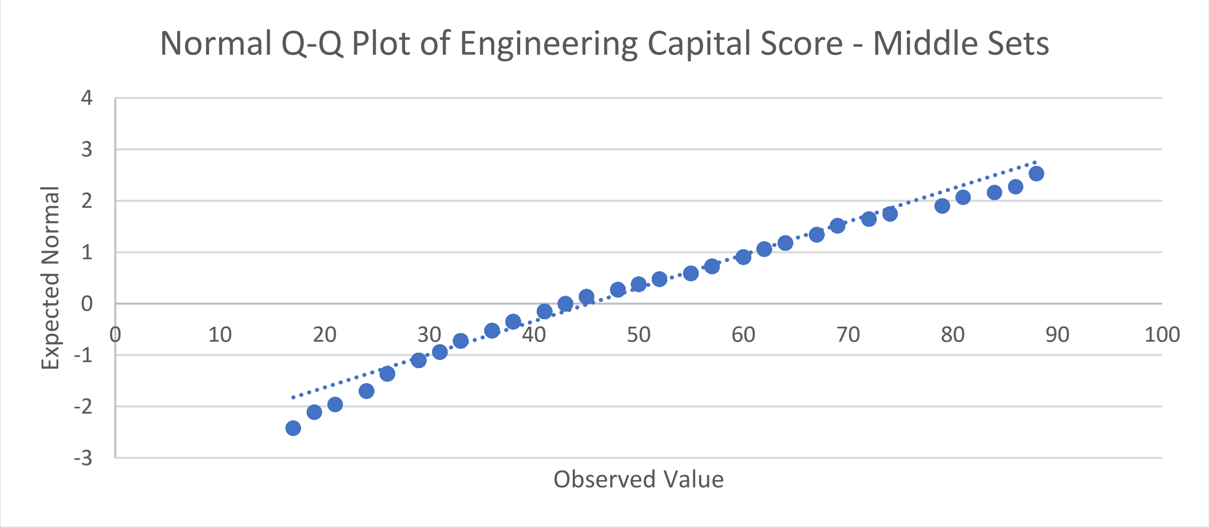
		Cases					
		Valid		Missing		Total	
	25.1.a. Science	N	Percent	N	Percent	N	Percent
Eng. Cap. Score.	There are not sets at this school/for this subject	183	100.0%	0	0.0%	183	100.0%
	Top	407	100.0%	0	0.0%	407	100.0%
	Middle	259	100.0%	0	0.0%	259	100.0%
	Bottom	48	100.0%	0	0.0%	48	100.0%

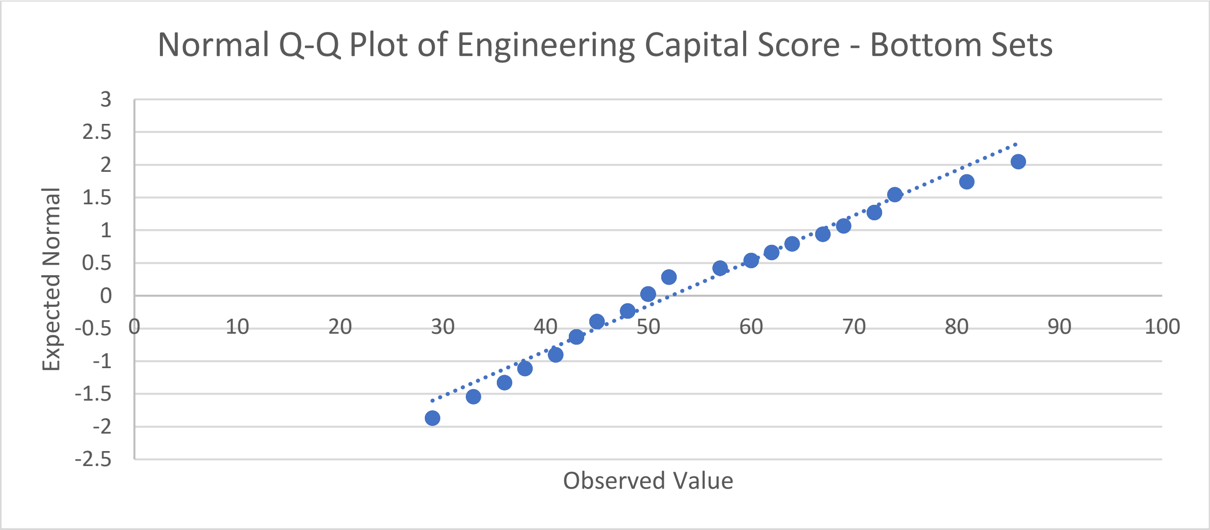
Descriptives

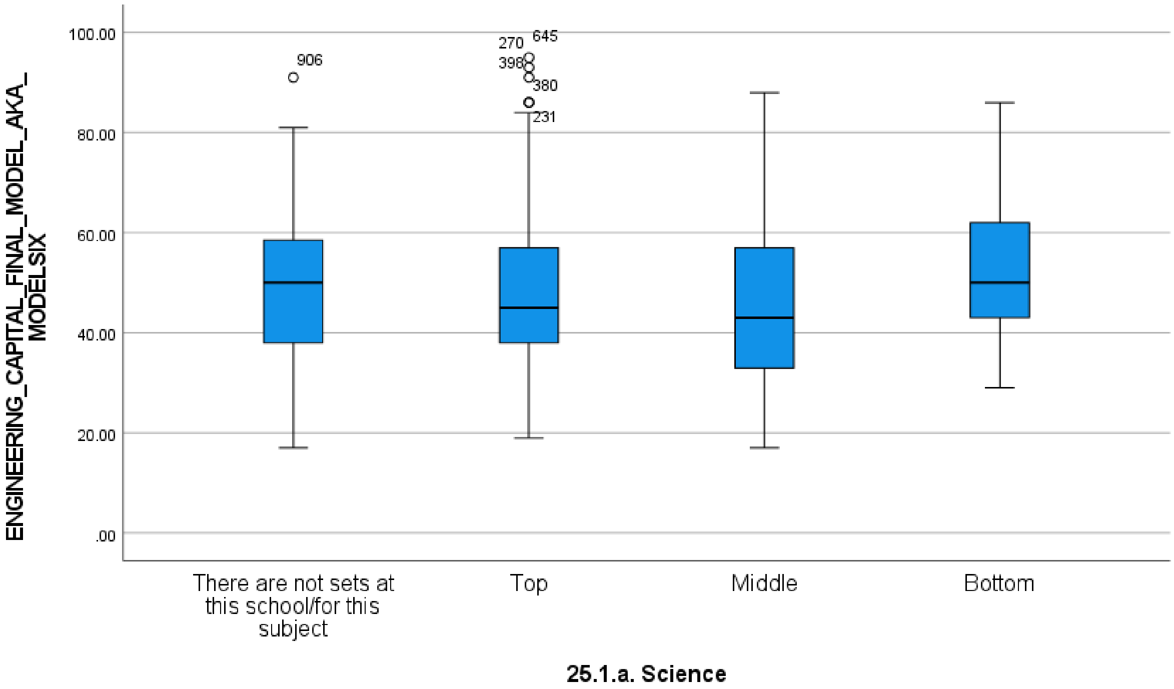
			25.1.a. Science							
			There are not sets at this school/for this subject		Top		Middle		Bottom	
			Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error
Eng. Cap. Score.	Mean		49.5628	1.02668	47.8280	.70572	45.3089	.93285	52.2500	1.92927
	95% Confidence Interval for Mean	Lower Bound	47.5371		46.4407		43.4719		48.3688	
		Upper Bound	51.5886		49.2153		47.1459		56.1312	
	5% Trimmed Mean		49.2747		47.2973		44.7439		51.8565	
	Median		50.0000		45.0000		43.0000		50.0000	
	Variance		192.896		202.704		225.385		178.660	
	Std. Deviation		13.88869		14.23743		15.01282		13.36636	
	Minimum		17.00		19.00		17.00		29.00	
	Maximum		91.00		95.00		88.00		86.00	
	Range		74.00		76.00		71.00		57.00	
	Interquartile Range		22.00		19.00		24.00		19.00	
	Skewness		.342	.180	.577	.121	.504	.151	.527	.343
	Kurtosis		-.136	.357	.083	.241	-.226	.302	-.220	.674


Normal Q-Q Plot of Engineering Capital Score - No Sets
Expected Normal
4
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
90
100
Observed Value


Normal Q-Q Plot of Engineering Capital Score - Top Sets
Expected Normal
4
3
2
1
0
-1
-2
-3
-4
0
10
20
30
40
50
60
70
80
90
100
Observed Value


Normal Q-Q Plot of Engineering Capital Score - Middle Sets
Expected Normal
4
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
90
100
Observed Value


Normal Q-Q Plot of Engineering Capital Score - Bottom Sets
Expected Normal
3
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
0
10
20
30
40
50
60
70
80
90
100
Observed Value


ENGINEERING_CAPITAL_FINAL_MODEL_AKA_MODELSIX
100.00
80.00
60.00
40.00
20.00
.00
906
270
645
398
380
231
There are not sets at this school/for this subject
Top
Middle
Bottom
25.1.a. Science

A one-way ANOVA was adopted to determine whether engineering capital scores differed between groups based on school science ability set. A total of 897 participants were classified into four groups based on educational science ability: No Sets at This School (N=183), Bottom Sets (N=48), Middle Sets (N=259), and Top Sets (N=407). Engineering capital scores were found to statistically differ (F(3, 893) = 5.043, p=0.002, ETA^2=0.017). Tukey post-hoc testing only revealed significant differences between the Middle & Bottom groups and Middle & No Sets groups. The ETA^2 size of 0. 017 indicates a small effect of science ability group in shaping engineering capital scores.

Descriptives

Eng. Cap. Score.

						95% Confidence Interval for Mean				Between-Component
		N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound	Minimum	Maximum	
No Sets		183	49.5628	13.88869	1.02668	47.5371	51.5886	17.00	91.00	
Top		407	47.8280	14.23743	.70572	46.4407	49.2153	19.00	95.00	
Middle		259	45.3089	15.01282	.93285	43.4719	47.1459	17.00	88.00	
Bottom		48	52.2500	13.36636	1.92927	48.3688	56.1312	29.00	86.00	
Total		897	47.6912	14.44924	.48245	46.7443	48.6380	17.00	95.00	
Model	Fixed Effects			14.35244	.47921	46.7507	48.6317			
	Random Effects				1.27463	43.6348	51.7476			4.18009

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Eng. Cap. Score.	Based on Mean	1.062	3	893	.364
	Based on Median	.920	3	893	.430
	Based on Median and with adjusted df	.920	3	888.924	.430
	Based on trimmed mean	.972	3	893	.405

ANOVA

Eng. Cap. Score.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3116.183	3	1038.728	5.043	.002
Within Groups	183951.278	893	205.992		
Total	187067.460	896			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
Eng. Cap. Score.	Eta-squared	.017	.003	.034
	Epsilon-squared	.013	-.001	.031
	Omega-squared Fixed-effect	.013	-.001	.031
	Omega-squared Random-effect	.004	.000	.011

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.

Multiple Comparisons

Eng. Cap. Scores.

	(I) 25.1.a. Science	(J) 25.1.a. Science	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Tukey HSD	There are not sets at this school/for this subject	Top	1.73483	1.27741	.526	-1.5531	5.0227
		Middle	4.25396*	1.38599	.012	.6866	7.8213
		Bottom	-2.68716	2.32748	.656	-8.6778	3.3035
	Top	There are not sets at this school/for this subject	-1.73483	1.27741	.526	-5.0227	1.5531
		Middle	2.51913	1.14082	.122	-.4172	5.4554
		Bottom	-4.42199	2.19035	.182	-10.0597	1.2157
	Middle	There are not sets at this school/for this subject	-4.25396*	1.38599	.012	-7.8213	-.6866
		Top	-2.51913	1.14082	.122	-5.4554	.4172
		Bottom	-6.94112*	2.25540	.012	-12.7462	-1.1360
	Bottom	There are not sets at this school/for this subject	2.68716	2.32748	.656	-3.3035	8.6778
		Top	4.42199	2.19035	.182	-1.2157	10.0597
		Middle	6.94112*	2.25540	.012	1.1360	12.7462

*. The mean difference is significant at the 0.05 level.

One-Way ANOVA: Mathematics Academic Ability and Engineering Capital Score

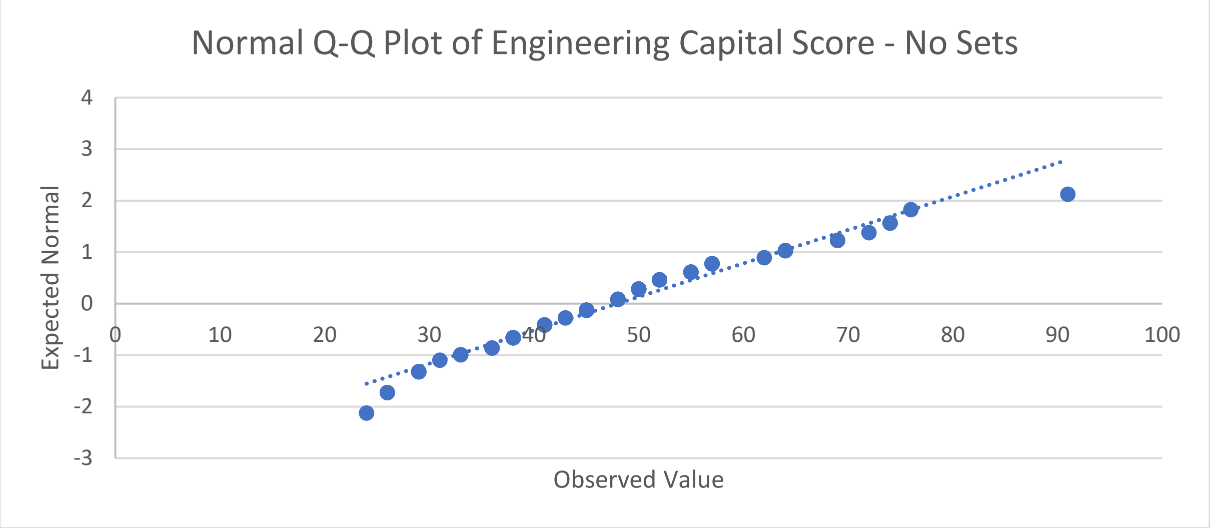
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1. The assumptions underpinning this test were met approving its use.

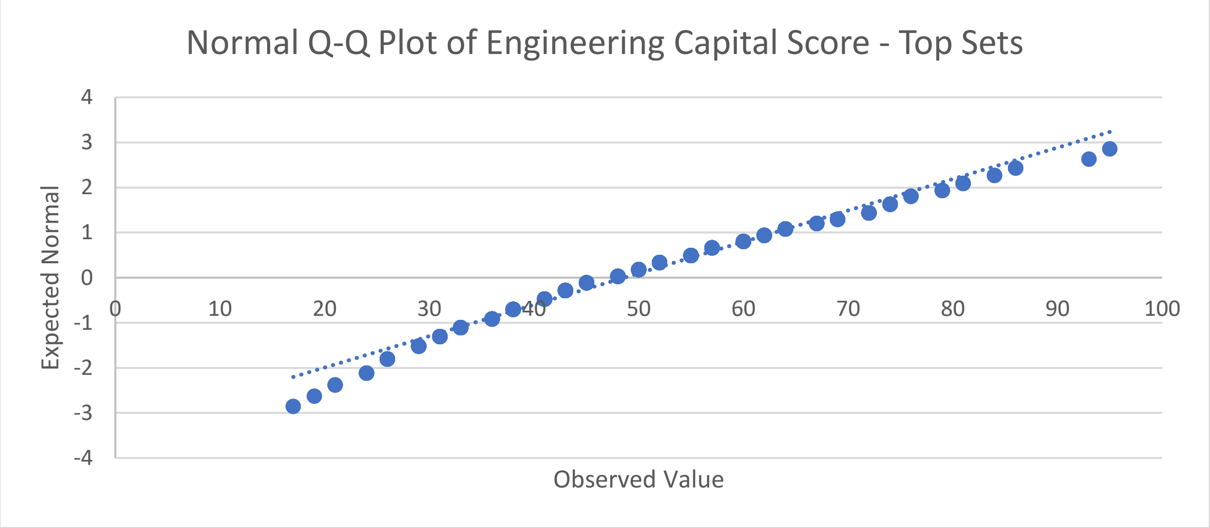
Case Processing Summary

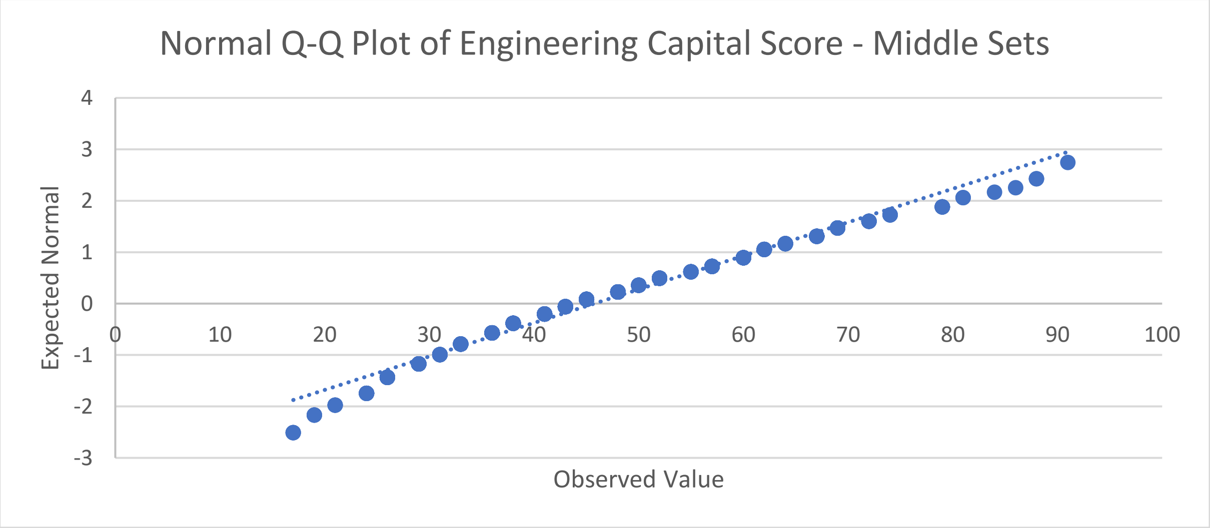
		Cases					
		Valid		Missing		Total	
	25.2.a. Maths	N	Percent	N	Percent	N	Percent
Eng. Cap. Score	There are not sets at this school/for this subject	58	100.0%	0	0.0%	58	100.0%
	Top	465	100.0%	0	0.0%	465	100.0%
	Middle	330	100.0%	0	0.0%	330	100.0%
	Bottom	48	100.0%	0	0.0%	48	100.0%

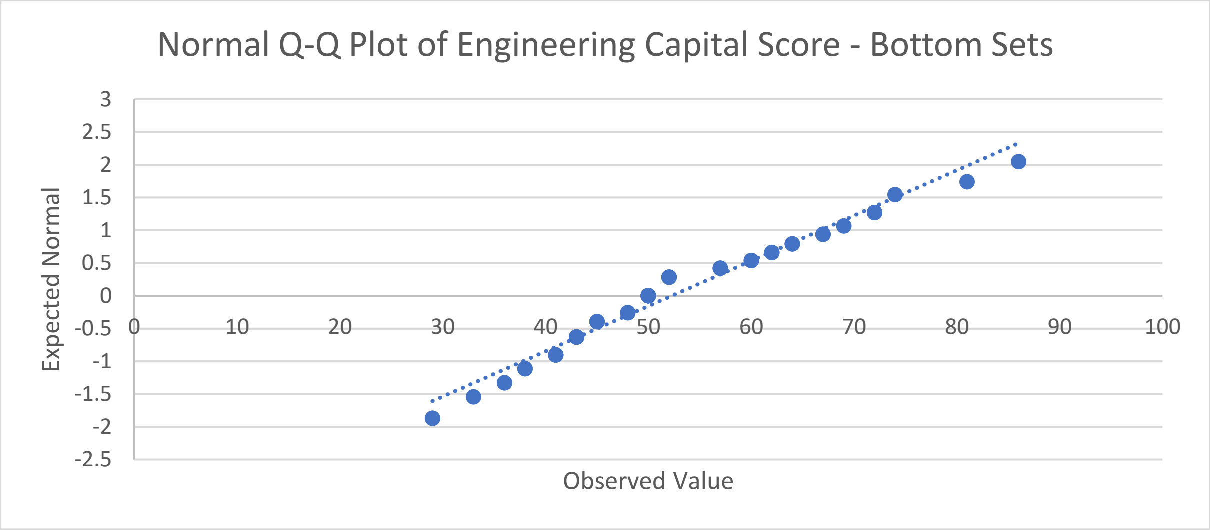
Descriptives

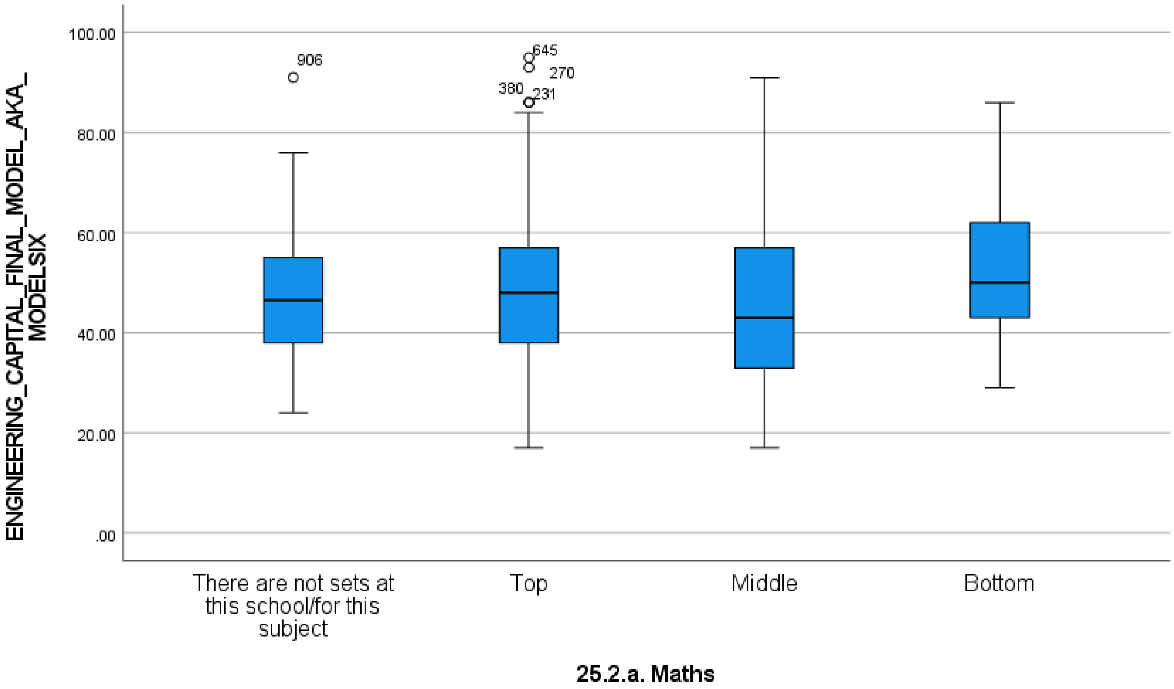
			Statistic				Std. Error			
			25.2.a. Maths				25.2.a. Maths			
			There are not sets at this school/for this subject	Top	Middle	Bottom	There are not sets at this school/for this subject	Top	Middle	Bottom
Eng. Cap. Score.	Mean		47.9655	48.6194	45.7667	52.2917	1.88154	.65159	.82116	1.92776
	95% Confidence Interval for Mean	Lower Bound	44.1978	47.3389	44.1513	48.4135				
		Upper Bound	51.7332	49.8998	47.3821	56.1698				
	5% Trimmed Mean		47.4138	48.2204	45.2121	51.9028				
	Median		46.5000	48.0000	43.0000	50.0000				
	Variance		205.332	197.426	222.520	178.381				
	Std. Deviation		14.32941	14.05083	14.91710	13.35594				
	Minimum		24.00	17.00	17.00	29.00				
	Maximum		91.00	95.00	91.00	86.00				
	Range		67.00	78.00	74.00	57.00				
	Interquartile Range		17.50	19.00	24.00	19.00				
	Skewness		.642	.457	.521	.519	.314	.113	.134	.343
	Kurtosis		.329	-.089	-.119	-.218	.618	.226	.268	.674


Normal Q-Q Plot of Engineering Capital Score - No Sets
Expected Normal
4
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
90
100
Observed Value


Normal Q-Q Plot of Engineering Capital Score - Top Sets
Expected Normal
4
3
2
1
0
-1
-2
-3
-4
0
10
20
30
40
50
60
70
80
90
100
Observed Value


Normal Q-Q Plot of Engineering Capital Score - Middle Sets
Expected Normal
4
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
90
100
Observed Value


Normal Q-Q Plot of Engineering Capital Score - Bottom Sets
Expected Normal
3
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
0
10
20
30
40
50
60
70
80
90
100
Observed Value


ENGINEERING_CAPITAL_FINAL_MODEL_AKA_MODELSIX
100.00
80.00
60.00
40.00
20.00
.00
906
645
270
380
231
There are not sets at this school/for this subject
Top
Middle
Bottom
25.2.a. Maths

A one-way ANOVA was adopted to determine whether engineering capital scores differed between groups based on school mathematics sets. A total of 901 participants were classified into four groups based on mathematics school sets: No Sets at This School (N=58), Bottom Sets (N=48), Middle Sets (N=330), and Top Sets (N=465). Engineering capital scores were found to statistically differ (F(3, 897) = 4.272, p=0.005, ETA^2=0.014). Tukey post-hoc testing revealed significant differences the Top & Middle and Middle & Bottom groups. The ETA^2 size of 0.014 indicates a small effect of mathematics ability groups in shaping engineering capital scores.

Descriptives

Eng. Cap. Score.

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum	Between-Component
						Lower Bound	Upper Bound			
No Sets		58	47.9655	14.32941	1.88154	44.1978	51.7332	24.00	91.00	
Top		465	48.6194	14.05083	.65159	47.3389	49.8998	17.00	95.00	
Middle		330	45.7667	14.91710	.82116	44.1513	47.3821	17.00	91.00	
Bottom		48	52.2917	13.35594	1.92776	48.4135	56.1698	29.00	86.00	
Total		901	47.7281	14.43546	.48092	46.7842	48.6719	17.00	95.00	
Model	Fixed Effects			14.35738	.47831	46.7893	48.6668			
	Random Effects				1.33163	43.4902	51.9659			3.79026

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Eng. Cap. Score.	Based on Mean	.831	3	897	.477
	Based on Median	.813	3	897	.487
	Based on Median and with adjusted df	.813	3	889.088	.487
	Based on trimmed mean	.776	3	897	.507

ANOVA

Eng. Cap. Score.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2641.873	3	880.624	4.272	.005
Within Groups	184902.507	897	206.134		
Total	187544.380	900			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
Eng. Cap. Score.	Eta-squared	.014	.001	.030
	Epsilon-squared	.011	-.002	.027
	Omega-squared Fixed-effect	.011	-.002	.027
	Omega-squared Random-effect	.004	-.001	.009

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.

Multiple Comparisons

Eng. Cap. Score.

	(I) 25.2.a. Maths	(J) 25.2.a. Maths	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Tukey HSD	There are not sets at this school/for this subject	Top	-.65384	1.99933	.988	-5.7998	4.4922
		Middle	2.19885	2.04418	.705	-3.0626	7.4603
		Bottom	-4.32615	2.80152	.411	-11.5368	2.8845
	Top	There are not sets at this school/for this subject	.65384	1.99933	.988	-4.4922	5.7998
		Middle	2.85269*	1.03342	.030	.1928	5.5126
		Bottom	-3.67231	2.17664	.331	-9.2747	1.9300
	Middle	There are not sets at this school/for this subject	-2.19885	2.04418	.705	-7.4603	3.0626
		Top	-2.85269*	1.03342	.030	-5.5126	-.1928
		Bottom	-6.52500*	2.21791	.018	-12.2336	-.8164
	Bottom	There are not sets at this school/for this subject	4.32615	2.80152	.411	-2.8845	11.5368
		Top	3.67231	2.17664	.331	-1.9300	9.2747
		Middle	6.52500*	2.21791	.018	.8164	12.2336

*. The mean difference is significant at the 0.05 level.

Independent Samples T-Test: National Context and Engineering Capital Score

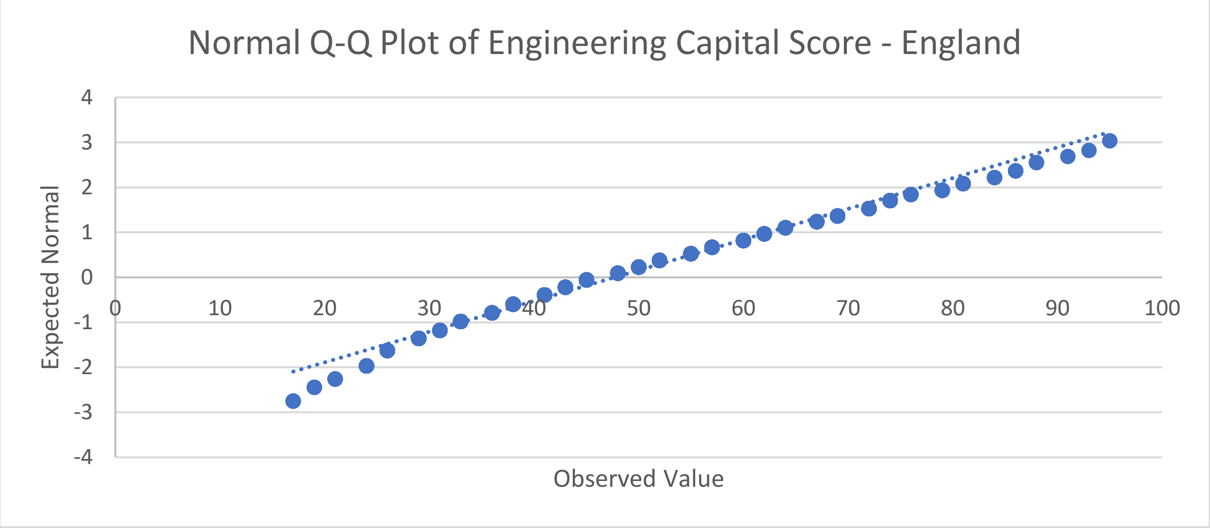
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1. The assumptions underpinning this test were met approving its use.

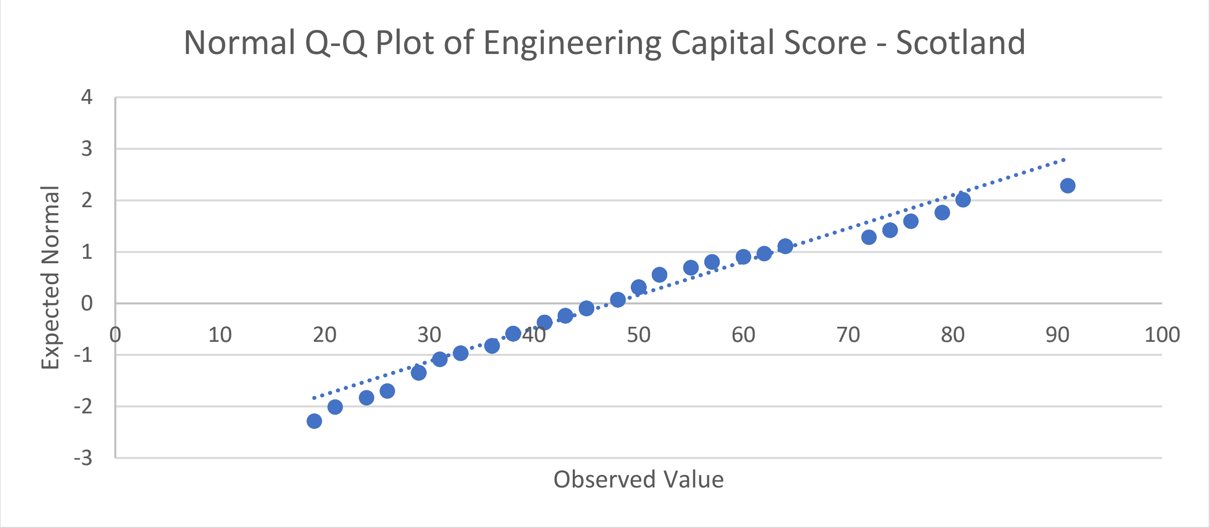
Case Processing Summary

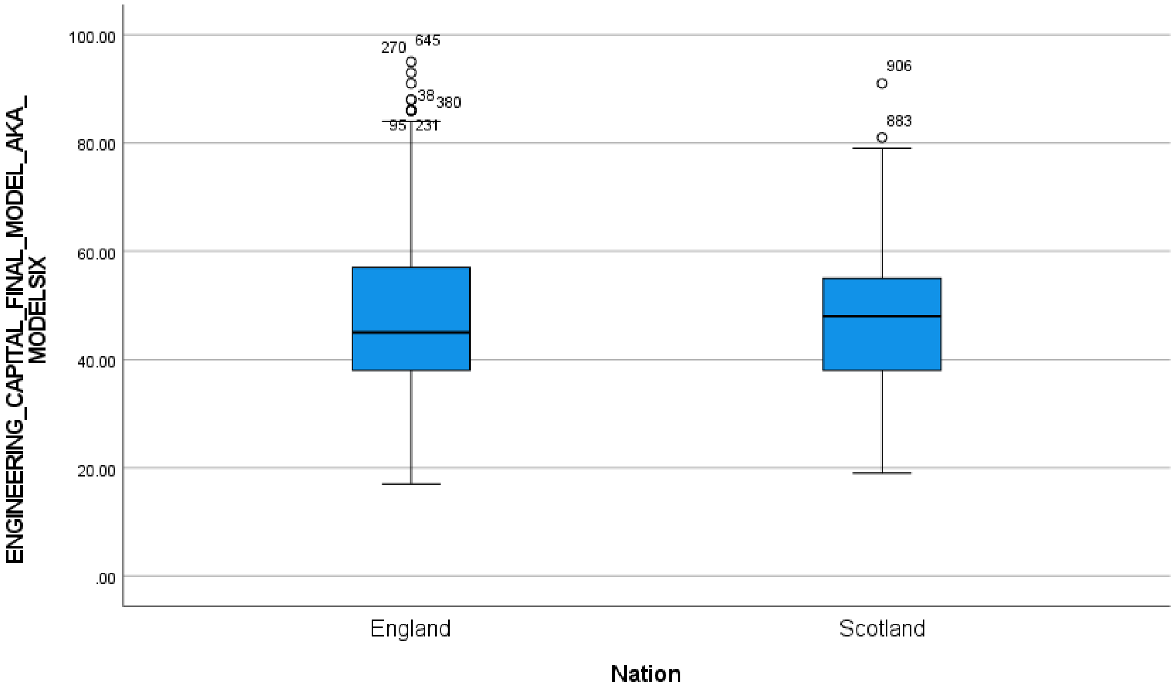
		Cases					
		Valid		Missing		Total	
	Nation	N	Percent	N	Percent	N	Percent
Eng. Cap. Score.	England	832	100.0%	0	0.0%	832	100.0%
	Scotland	89	100.0%	0	0.0%	89	100.0%

Descriptives

			Nation			
			England		Scotland	
			Statistic	Std. Error	Statistic	Std. Error
Eng. Cap. Score.	Mean		47.6995	.49944	47.4494	1.54867
	95% Confidence Interval for Mean	Lower Bound	46.7192		44.3718	
		Upper Bound	48.6798		50.5271	
	5% Trimmed Mean		47.2650		46.8883	
	Median		45.0000		48.0000	
	Variance		207.532		213.455	
	Std. Deviation		14.40596		14.61009	
	Minimum		17.00		19.00	
	Maximum		95.00		91.00	
	Range		78.00		72.00	
	Interquartile Range		19.00		17.00	
	Skewness		.430	.085	.634	.255
	Kurtosis		-.159	.169	.304	.506


Normal Q-Q Plot of Engineering Capital Score - England


Normal Q-Q Plot of Engineering Capital Score - Scotland



An independent samples t-test identified no significant difference in the engineering capital scores of those in England (N=832, M=47.70, SD=14.41) and Scotland (N=89, M=47.45, SD=14.61) (t(919)=0.155, p=0.877, d=0.017).

Group Statistics

	Nation	N	Mean	Std. Deviation	Std. Error Mean
Eng. Cap. Score.	England	832	47.6995	14.40596	.49944
	Scotland	89	47.4494	14.61009	1.54867

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Eng. Cap. Score	Equal variances assumed	.197	.657	.155	919	.438	.877	.25008	1.60882	-2.90731	3.40747
	Equal variances not assumed			.154	107.134	.439	.878	.25008	1.62721	-2.97562	3.47579

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
Eng. Cap. Score.	Cohen's d	14.42563	.017	-.201	.236
	Hedges' correction	14.43742	.017	-.201	.236
	Glass's delta	14.61009	.017	-.202	.236

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

Binary Logistic Regression: Engineering Educational Aspiration and Engineering Capital Score

A binary logistic regression was adopted to determine the effect of engineering capital score on the likelihood of aspiring to engineering education. Statistical assumptions were tested and confirmed the linearity of the relationship between the IV and DV logit, a lack of significant multicollinearity and lack of influential outliers supporting the use of this procedure. The logistic regression model was statistically significant, χ2(1) = 271.705, p<0.001. The model explained 38.8% (Nagelkerke R^2) of the variance in educational aspiration and correctly classified 80.6% of cases. Sensitivity was 48.2%, specificity was 91.8%. Increasing engineering capital score was associated with a greater likelihood of aspiring to engineering educational pathways.

Classification Table[a,b]

			Predicted		
			Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no		Percentage Correct
	Observed		No	Yes	
Step 0	Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no	No	659	0	100.0
		Yes	228	0	.0
	Overall Percentage				74.3

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-1.061	.077	190.826	1	.000	.346

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Eng. Cap. Score.	250.286	1	.000
	Overall Statistics		250.286	1	.000

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	271.705	1	.000
	Block	271.705	1	.000
	Model	271.705	1	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	739.377[a]	.264	.388

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	6.261	7	.510

Classification Table[a]

			Predicted		
			Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no		Percentage Correct
	Observed		No	Yes	
Step 1	Binary Coded: Yes at University or A-level or after GCSE, No at unsure and no	No	605	54	91.8
		Yes	118	110	48.2
	Overall Percentage				80.6

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Eng. Cap. Score.	.107	.008	174.238	1	.000	1.113
	Constant	-6.622	.449	217.122	1	.000	.001

a. Variable(s) entered on step 1: ENGINEERING_CAPITAL_FINAL_MODEL_AKA_MODELSIX.

Binary Logistic Regression: Engineering Career Aspiration and Engineering Capital Score

A binary logistic regression was adopted to determine the effect of engineering capital score on the likelihood of aspiring to engineering-related careers. Statistical assumptions were tested and confirmed the linearity of the relationship between the IV and DV logit, a lack of significant multicollinearity and lack of influential outliers supporting the use of this procedure. The logistic regression model was statistically significant, χ2(1) = 374.683, p<0.001. The model explained 47.1% (Nagelkerke R^2) of the variance in career aspiration and correctly classified 80.0% of cases. Sensitivity was 67.4%, specificity was 87.0%. Increasing engineering capital score was associated with a greater likelihood of aspiring to engineering career pathways.

Classification Table[a,b]

			Predicted		
			57. Do you think you might like to work in an engineering-related job in the future?		Percentage Correct
	Observed		No	Yes	
Step 0	57. Do you think you might like to work in an engineering-related job in the future?	No	576	0	100.0
		Yes	316	0	.0
	Overall Percentage				64.6

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.600	.070	73.549	1	.000	.549

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Eng. Cap. Score.	319.496	1	.000
	Overall Statistics		319.496	1	.000

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	374.683	1	.000
	Block	374.683	1	.000
	Model	374.683	1	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	784.996[a]	.343	.471

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	9.904	7	.194

Classification Table[a]

	Observed		Predicted: 57. Do you think you might like to work in an engineering-related job in the future? No	Predicted: 57. Do you think you might like to work in an engineering-related job in the future? Yes	Percentage Correct
Step 1	57. Do you think you might like to work in an engineering-related job in the future?	No	501	75	87.0
		Yes	103	213	67.4
	Overall Percentage				80.0

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Eng. Cap. Score.	.127	.009	209.405	1	.000	1.136
	Constant	-6.955	.457	231.987	1	.000	.001

a. Variable(s) entered on step 1: ENGINEERING_CAPITAL_FINAL_MODEL_AKA_MODELSIX.

Directory of Statistical Analyses Outputs for Chapter Eight

Cronbach’s Alpha Analysis: Engineering Habits of Mind Instrument

A Cronbach’s Alpha analysis was utilised to examine the internal consistency (reliability) of responses on the engineering habits of mind scale. Six items were examined and determined to possess a high level of internal consistency (N=897, a=0.850) supporting the use of this scale. This result was not meaningfully improved by the removal of any of the items.

Case Processing Summary

		N	%
Cases	Valid	897	97.4
	Excluded[a]	24	2.6
	Total	921	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.850	.852	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
41.1. I am good at finding patterns and seeing how things fit together	3.04	11.003	.648	.464	.823
41.2. I am good at looking for problems and checking things are right	3.03	10.769	.705	.542	.812
41.3. I am good at imagining and picturing what things might look like	2.81	11.550	.492	.272	.853
41.4. I am good at trying different ways to make things better	3.01	10.940	.676	.475	.817
41.5. I am good at fixing problems and finding solutions	3.03	11.074	.668	.490	.819
41.6. I am good at trying things, testing ideas, and changing my plans if necessary	3.08	11.055	.628	.421	.826

Principal Components Analysis: Engineering Habits of Mind Instrument

A Principal Components Analysis (PCA) was run on a six-item instrument measuring the engineering habits of mind of 897 participants. The suitability of PCA was confirmed with a Kaiser-Meyer-Olkin (KMO) measure of 0.861 and a statistically significant Bartlett’s test ($p<0.001$).

The PCA resolved to a single component with an eigenvalue greater than one which explained 57.76% of total variance. No rotation was applied. This result aligns with the theoretical structure of the instrument supporting its validity and adoption.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.861
Bartlett's Test of Sphericity	Approx. Chi-Square	2112.931
	df	15
	Sig.	.000

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.466	57.759	57.759	3.466	57.759	57.759
2	.732	12.205	69.964			
3	.618	10.292	80.256			
4	.461	7.683	87.939			
5	.393	6.548	94.487			
6	.331	5.513	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component
	1
41.1. I am good at finding patterns and seeing how things fit together	.768
41.2. I am good at looking for problems and checking things are right	.818
41.3. I am good at imagining and picturing what things might look like	.621
41.4. I am good at trying different ways to make things better	.789
41.5. I am good at fixing problems and finding solutions	.791
41.6. I am good at trying things, testing ideas, and changing my plans if necessary	.756

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Cronbach’s Alpha Analysis: Engineering Engagement Instrument

A Cronbach’s Alpha analysis was utilised to examine the internal consistency (reliability) of responses on the engineering engagement scale. Twelve items were examined and determined to possess a high level of internal consistency (N=851, a=0.922) supporting the use of this scale. This result was not meaningfully improved by the removal of any of the items.

Case Processing Summary

		N	%
Cases	Valid	851	92.4
	Excluded[a]	70	7.6
	Total	921	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.922	.919	12

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
63.a.1. I believe I could be successful at engineering in the future	.36	78.007	.804	.681	.909
63.a.2. I think understanding engineering is important	-.09	80.646	.746	.769	.912
63.a.3. I enjoy learning about engineering	.22	77.286	.879	.870	.906
63.a.4. I think learning about engineering is interesting	.15	77.225	.871	.864	.906
63.a.5. I think it is useful to know about engineering	-.14	80.068	.757	.796	.912
63.a.6. Learning about engineering takes too much effort	-.11	89.223	.307	.437	.929
63.a.7. I think learning about engineering is boring	-.16	83.946	.536	.539	.921
63.a.8. I worry I am not good at engineering	.01	94.402	.029	.225	.939
63.a.9. I want to learn more about engineering	.15	77.405	.844	.828	.907
63.a.10. I want to learn more about engineering, even if it is hard	.19	77.436	.855	.846	.907
63.a.11. It would be good for my future to learn about engineering	.03	79.021	.775	.755	.911
40.7. I know quite a lot about engineering	.64	81.766	.694	.508	.914

Principal Components Analysis: Engineering Engagement Instrument

A Principal Components Analysis (PCA) was run on the twelve-item instrument measuring the engineering engagement of 851 participants. The suitability of PCA was confirmed with a Kaiser-Meyer-Olkin (KMO) measure of 0.920 and a statistically significant Bartlett's test (p<0.001). The PCA resolved to two components with an eigenvalue greater than one which explained 73.86% of total variance. No rotation was applied.

This test aligns with the theoretical structure of the instrument supporting its validity and adoption. Whilst the instrument did not resolve to a single component the two components align to the theoretical expectation of engineering engagement as discussed in Chapter Eight.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.920
Bartlett's Test of Sphericity	Approx. Chi-Square	9537.519
	df	66
	Sig.	.000

Communalities

	Initial	Extraction
40.7. I know quite a lot about engineering	1.000	.562
63.a.1. I believe I could be successful at engineering in the future	1.000	.721
63.a.2. I think understanding engineering is important	1.000	.738
63.a.3. I enjoy learning about engineering	1.000	.847
63.a.4. I think learning about engineering is interesting	1.000	.842
63.a.5. I think it is useful to know about engineering	1.000	.774
63.a.6. Learning about engineering takes too much effort	1.000	.698
63.a.7. I think learning about engineering is boring	1.000	.727
63.a.8. I worry I am not good at engineering	1.000	.528
63.a.9. I want to learn more about engineering	1.000	.822
63.a.10. I want to learn more about engineering, even if it is hard	1.000	.825
63.a.11. It would be good for my future to learn about engineering	1.000	.778

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.101	59.175	59.175	7.101	59.175	59.175
2	1.762	14.685	73.860	1.762	14.685	73.860
3	.742	6.182	80.041			
4	.535	4.459	84.501			
5	.416	3.463	87.964			
6	.368	3.063	91.027			
7	.330	2.749	93.776			
8	.256	2.135	95.911			
9	.169	1.411	97.322			
10	.134	1.114	98.436			
11	.106	.883	99.320			
12	.082	.680	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component	
	1	2
40.7. I know quite a lot about engineering	.742	.106
63.a.1. I believe I could be successful at engineering in the future	.848	.039
63.a.2. I think understanding engineering is important	.831	-.218
63.a.3. I enjoy learning about engineering	.921	-.008
63.a.4. I think learning about engineering is interesting	.917	-.021
63.a.5. I think it is useful to know about engineering	.845	-.244
63.a.6. Learning about engineering takes too much effort	.285	.786
63.a.7. I think learning about engineering is boring	.525	.672
63.a.8. I worry I am not good at engineering	-.009	.727
63.a.9. I want to learn more about engineering	.904	-.073
63.a.10. I want to learn more about engineering, even if it is hard	.908	-.037
63.a.11. It would be good for my future to learn about engineering	.860	-.196

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

One-Way ANOVA: Engineering Habits of Mind

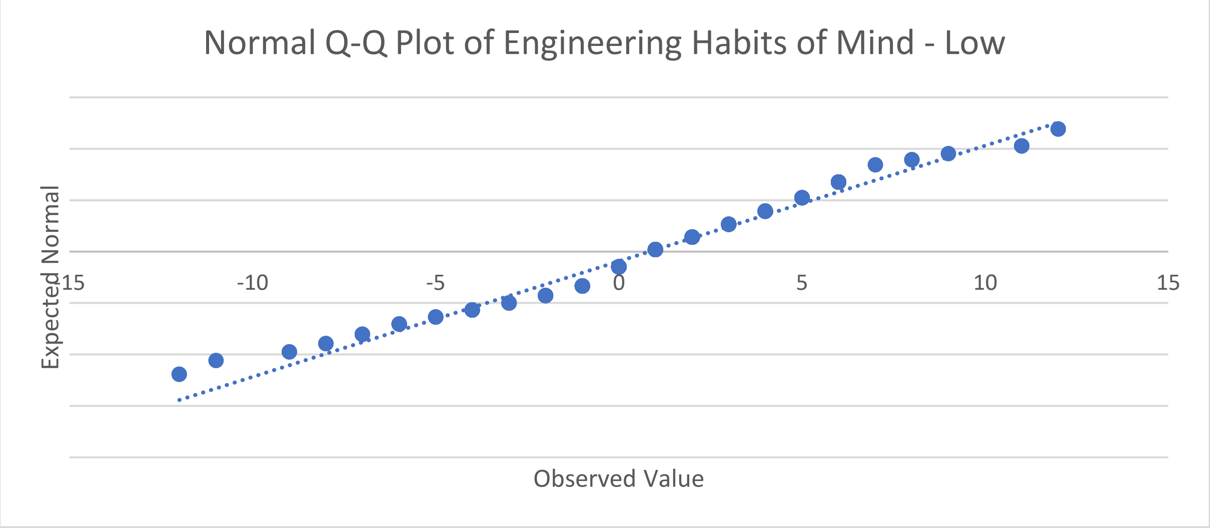
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be largely normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1 – the Medium group did express slightly greater kurtosis however this was deemed within an acceptable margin given the robustness of the ANOVA procedure. The assumptions underpinning this test were met approving its use.

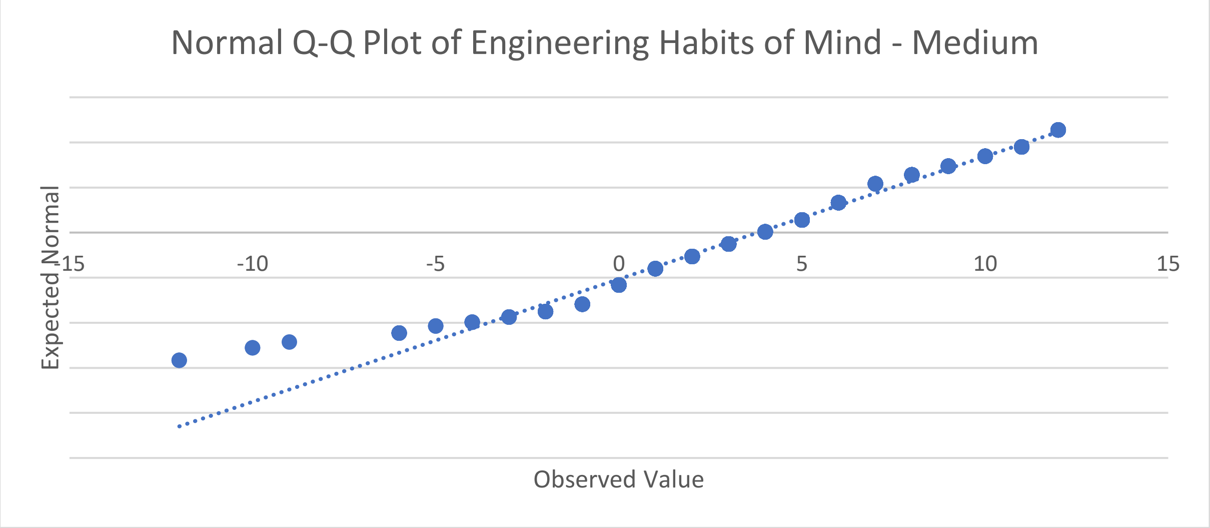
Case Processing Summary

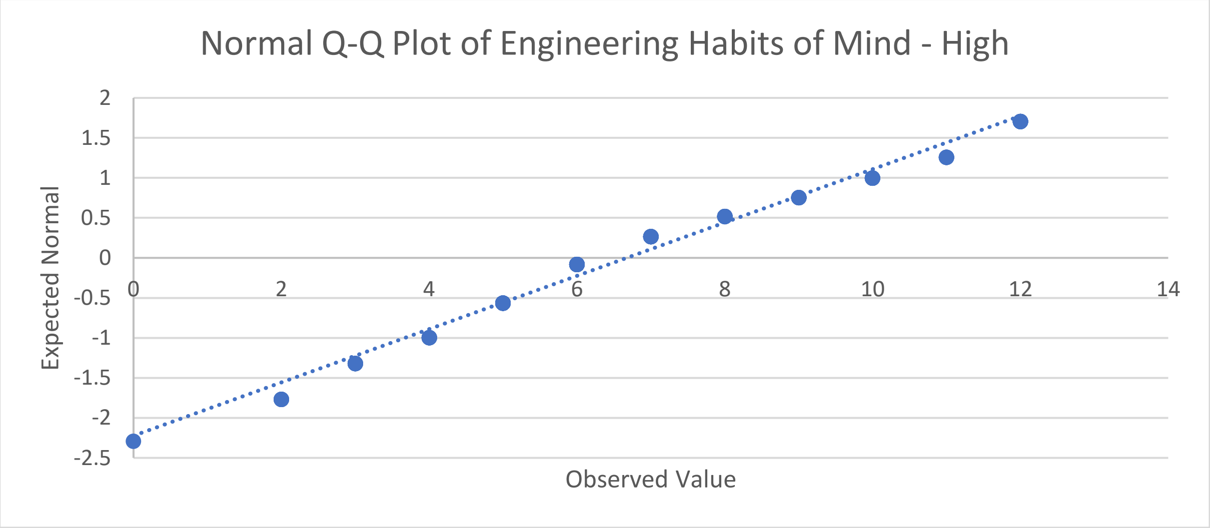
		Cases					
	ENGINEERING_CAPITAL_FINAL_GROUPS	Valid		Missing		Total	
		N	Percent	N	Percent	N	Percent
Engineering Habits of Mind	Low	175	100.0%	0	0.0%	175	100.0%
	Medium	656	100.0%	0	0.0%	656	100.0%
	High	90	100.0%	0	0.0%	90	100.0%

Descriptives

			ENGINEERING_CAPITAL_FINAL_GROUPS					
			Low		Medium		High	
			Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error
Engineering Habits of Mind	Mean		.83	.322	3.79	.139	6.67	.295
	95% Confidence Interval for Mean	Lower Bound	.19		3.52		6.08	
		Upper Bound	1.46		4.06		7.25	
	5% Trimmed Mean		.91		3.84		6.65	
	Median		1.00		4.00		6.00	
	Variance		18.131		12.597		7.843	
	Std. Deviation		4.258		3.549		2.800	
	Minimum		-12		-12		0	
	Maximum		12		12		12	
	Range		24		24		12	
	Interquartile Range		5		4		4	
	Skewness		-.372	.184	-.450	.095	.266	.254
	Kurtosis		.871	.365	1.680	.191	-.483	.503


Normal Q-Q Plot of Engineering Habits of Mind - Low
Expected Normal
-15
-10
-5
0
5
10
15
Observed Value


Normal Q-Q Plot of Engineering Habits of Mind - Medium
Expected Normal
-15
-10
-5
0
5
10
15
Observed Value


Normal Q-Q Plot of Engineering Habits of Mind - High
Expected Normal
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
0
2
4
6
8
10
12
14
Observed Value

A one-way Welch’s ANOVA was adopted to determine whether engineering habits of mind scores differed between groups based on engineering capital. A total of 921 participants were classified into three groups based on engineering capital scores: Low (N=175), Medium (N=656), and High (N=90). Engineering habits of mind scores were found to statistically differ (F(2, 214.224) = 89.394, p<0.001, ETA^2=0.154). Games-Howell post-hoc testing revealed significant differences at all levels between the Low (M=0.83, SD=4.26), Medium (M=3.79, SD=3.55) and High (M=6.67, SD=2.80) groups. The ETA^2 size of 0.154 indicates a strong effect of engineering capital in shaping engineering habits of mind scores.

Descriptives

Engineering Habits of Mind

						95% Confidence Interval for Mean				
		N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound	Minimum	Maximum	Between-Component Variance
Low		175	.83	4.258	.322	.19	1.46	-12	12	
Medium		656	3.79	3.549	.139	3.52	4.06	-12	12	
High		90	6.67	2.800	.295	6.08	7.25	0	12	
Total		921	3.51	3.944	.130	3.25	3.76	-12	12	
Model	Fixed Effects			3.631	.120	3.27	3.74			
	Random Effects				1.715	-3.87	10.89			5.295

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Engineering Habits of Mind	Based on Mean	4.893	2	918	.008
	Based on Median	5.351	2	918	.005
	Based on Median and with adjusted df	5.351	2	871.434	.005
	Based on trimmed mean	4.859	2	918	.008

ANOVA

Engineering Habits of Mind

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2206.362	2	1103.181	83.669	<.001
Within Groups	12103.827	918	13.185		
Total	14310.189	920			

ANOVA Effect Sizes[a]

		Point Estimate	95% Confidence Interval	
			Lower	Upper
Engineering Habits of Mind	Eta-squared	.154	.113	.195
	Epsilon-squared	.152	.111	.193
	Omega-squared Fixed-effect	.152	.111	.193
	Omega-squared Random-effect	.082	.059	.107

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

Robust Tests of Equality of Means

Engineering Habits of Mind

	Statistic[a]	df1	df2	Sig.
Welch	89.394	2	214.224	<.001
Brown-Forsythe	86.909	2	353.683	<.001

a. Asymptotically F distributed.

Multiple Comparisons

Dependent Variable: Engineering Literacy Total (EngCap+)

	(I) (II) (III) (IV) ENGINEERING_CAPITAL_FINAL_GROUPS	(J) ENGINEERING_CAPITAL_FINAL_GROUPS	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Tukey HSD	Low	Medium	-2.961*	.309	<.001	-3.69	-2.24
		High	-5.838*	.471	<.001	-6.94	-4.73
	Medium	Low	2.961*	.309	<.001	2.24	3.69
		High	-2.877*	.408	<.001	-3.84	-1.92
	High	Low	5.838*	.471	<.001	4.73	6.94
		Medium	2.877*	.408	<.001	1.92	3.84
Games-Howell	Low	Medium	-2.961*	.350	<.001	-3.79	-2.13
		High	-5.838*	.437	<.001	-6.87	-4.81
	Medium	Low	2.961*	.350	<.001	2.13	3.79
		High	-2.877*	.326	<.001	-3.65	-2.10
	High	Low	5.838*	.437	<.001	4.81	6.87
		Medium	2.877*	.326	<.001	2.10	3.65

*. The mean difference is significant at the 0.05 level.

Chi-Squared Test: Knowing a Hobbyist Engineer and Engineering Capital Groups

A Chi-Square Test was adopted to test the association between engineering capital groups and knowing a hobbyist engineer. Test assumptions were met with all expected cell frequencies greater than five. The test revealed a significant association, ($X^2(4)=34.084$, $p<0.001$, Cramer's V=0.137) with the Cramer's V score supporting a substantial relationship between categories. This supports a significant relationship between knowing a hobbyist engineering and engineering capital.

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
ENGINEERING_CAPITAL_FINAL_GROUPS * 37. Do you know anyone (family, friends, or community) who has a hobby that involves engineering e.g. designing or making things, woodworking, crafts, DIY?	903	98.0%	18	2.0%	921	100.0%

ENGINEERING_CAPITAL_GROUPS * 37. Do you know anyone (family, friends, or community) who has a hobby that involves engineering e.g. designing or making things, woodworking, crafts, DIY? Crosstabulation

			37. Do you know anyone (family, friends, or community) …			
			No	Yes	Don't Know	Total
ENGINEERING CAPITAL GROUPS	High	Count	16	62	9	87
		% within ENGINEERING_CAPITAL_FINAL_GROUPS	18.4%	71.3%	10.3%	100.0%
		% within 37. Do you know anyone (family, friends, or community) …	7.2%	12.4%	5.0%	9.6%
		% of Total	1.8%	6.9%	1.0%	9.6%
	Low	Count	66	67	37	170
		% within ENGINEERING_ CAPITAL_FINAL_GROUPS	38.8%	39.4%	21.8%	100.0%
		% within 37. Do you know anyone (family, friends, or community) …	29.6%	13.4%	20.7%	18.8%
		% of Total	7.3%	7.4%	4.1%	18.8%
	Medium	Count	141	372	133	646
		% within ENGINEERING_ CAPITAL_FINAL_GROUPS	21.8%	57.6%	20.6%	100.0%
		% within 37. Do you know anyone (family, friends, or community) …	63.2%	74.3%	74.3%	71.5%
		% of Total	15.6%	41.2%	14.7%	71.5%
Total		Count	223	501	179	903
		% within ENGINEERING_ CAPITAL_FINAL_GROUPS	24.7%	55.5%	19.8%	100.0%
		% within 37. Do you know anyone (family, friends, or community) …	100.0%	100.0%	100.0%	100.0%
		% of Total	24.7%	55.5%	19.8%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	34.084[a]	4	<.001
Likelihood Ratio	33.649	4	<.001
N of Valid Cases	903		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 17.25.

Chi-Squared Test: Knowing a Hobbyist Engineer and Gender

A Chi-Square Test was adopted to test the association between gender groups and knowing a hobbyist engineer. Test assumptions were met with all expected cell frequencies greater than five. The test revealed no significant association, ($X^2(2)=1.819$, p=0.403, Cramer's V=0.046).

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
2. Are you a girl or a boy? * 37. Do you know anyone (family, friends, or community) who has a hobby that involves engineering e.g. designing or making things, woodworking, crafts, DIY?	876	95.1%	45	4.9%	921	100.0%

2. Are you a girl or a boy? * 37. Do you know anyone (family, friends, or community) who has a hobby that involves engineering e.g. designing or making things, woodworking, crafts, DIY? Crosstabulation

			37. Do you know anyone (family, friends, or community)…			
			No	Yes	Don't Know	Total
2. Are you a girl or a boy?	Boy	Count	96	201	83	380
		% within 2. Are you a girl or a boy?	25.3%	52.9%	21.8%	100.0%
		% within 37. Do you know anyone (family, friends, or community) …	44.0%	41.6%	47.4%	43.4%
		% of Total	11.0%	22.9%	9.5%	43.4%
	Girl	Count	122	282	92	496
		% within 2. Are you a girl or a boy?	24.6%	56.9%	18.5%	100.0%
		% within 37. Do you know anyone (family, friends, or community) …	56.0%	58.4%	52.6%	56.6%
		% of Total	13.9%	32.2%	10.5%	56.6%
Total		Count	218	483	175	876
		% within 2. Are you a girl or a boy?	24.9%	55.1%	20.0%	100.0%
		% within 37. Do you know anyone (family, friends, or community) …	100.0%	100.0%	100.0%	100.0%
		% of Total	24.9%	55.1%	20.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	1.819[a]	2	.403
Likelihood Ratio	1.814	2	.404
Linear-by-Linear Association	.332	1	.564
N of Valid Cases	876		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 75.91.

Chi-Squared Test: Knowing a Hobbyist Engineer and Deprivation (Cultural Capital)

A Chi-Square Test was adopted to test the association between social class groups and knowing a hobbyist engineer. One test assumption was not met as not all cell frequencies were greater than five. The test revealed no significant association, ($X^2(8)=7.501$, $p=0.484$, Cramer’s $V=0.064$)

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
General Cultural Capital Category * 37. Do you know anyone (family, friends, or community) …	903	98.0%	18	2.0%	921	100.0%

General Cultural Capital Category * 37. Do you know anyone (family, friends, or community) who has a hobby that involves engineering e.g. designing or making things, woodworking, crafts, DIY? Crosstabulation

			37. Do you know anyone (family, friends, or community) …			
			No	Yes	Don't Know	Total
General Cultural Capital Category	Very low	Count	3	5	2	10
		% within General Cultural Capital	30.0%	50.0%	20.0%	100.0%
		% within 37. Do you know anyone …	1.3%	1.0%	1.1%	1.1%
		% of Total	0.3%	0.6%	0.2%	1.1%
	Low	Count	28	53	24	105
		% within General Cultural Capital	26.7%	50.5%	22.9%	100.0%
		% within 37. Do you know anyone…	12.6%	10.6%	13.4%	11.6%
		% of Total	3.1%	5.9%	2.7%	11.6%
	Medium	Count	91	172	72	335
		% within General Cultural Capital	27.2%	51.3%	21.5%	100.0%
		% within 37. Do you know …	40.8%	34.3%	40.2%	37.1%
		% of Total	10.1%	19.0%	8.0%	37.1%
	High	Count	65	170	54	289
		% within General Cultural Capital	22.5%	58.8%	18.7%	100.0%
		% within 37. Do you know anyone…	29.1%	33.9%	30.2%	32.0%
		% of Total	7.2%	18.8%	6.0%	32.0%
	Very high	Count	36	101	27	164
		% within General Cultural Capital	22.0%	61.6%	16.5%	100.0%
		% within 37. Do you know anyone …	16.1%	20.2%	15.1%	18.2%
		% of Total	4.0%	11.2%	3.0%	18.2%
Total		Count	223	501	179	903
		% within General Cultural Capital	24.7%	55.5%	19.8%	100.0%
		% within 37. Do you know anyone … ..	100.0%	100.0%	100.0%	100.0%
		% of Total	24.7%	55.5%	19.8%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	7.501[a]	8	.484
Likelihood Ratio	7.520	8	.482
Linear-by-Linear Association	.003	1	.959
N of Valid Cases	903		

a. 2 cells (13.3%) have expected count less than 5. The minimum expected count is 1.98.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.091	.484
	Cramer's V	.064	.484
N of Valid Cases		903	

One-Way ANOVA: Familial Capital

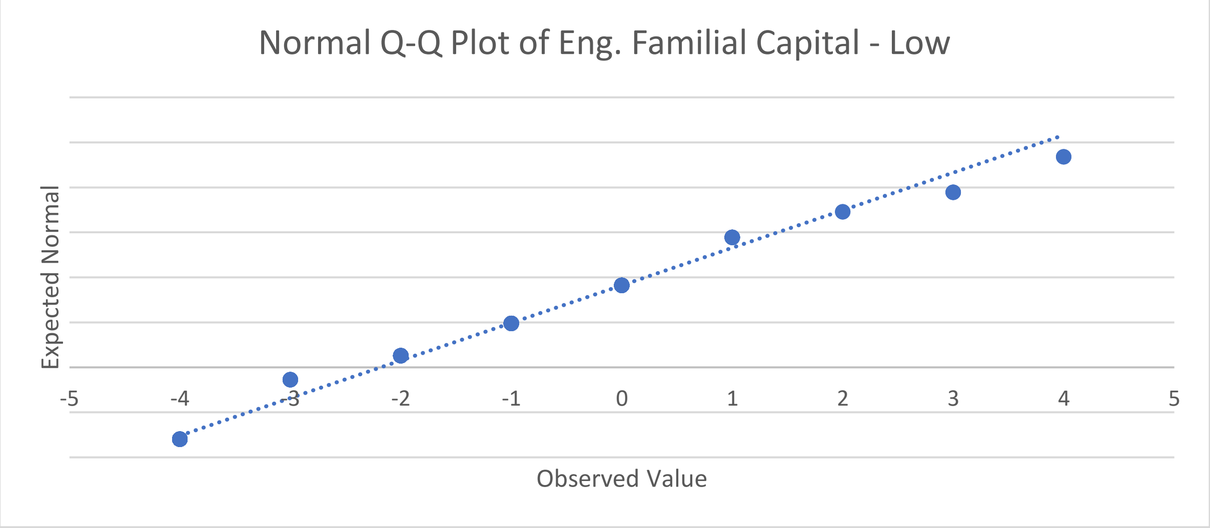
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be largely normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1. The assumptions underpinning this test were met approving its use.

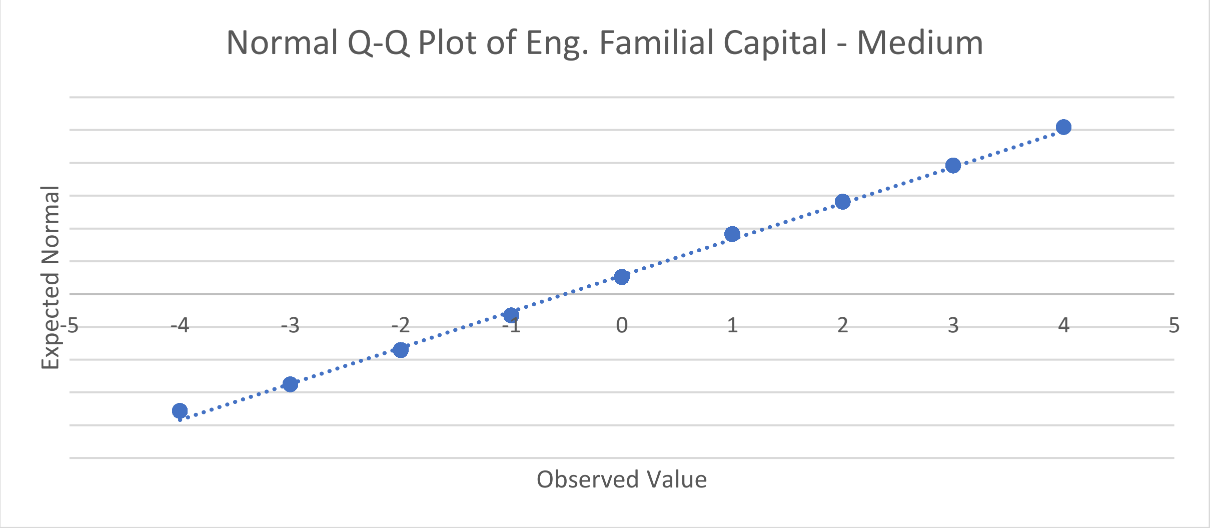
Case Processing Summary

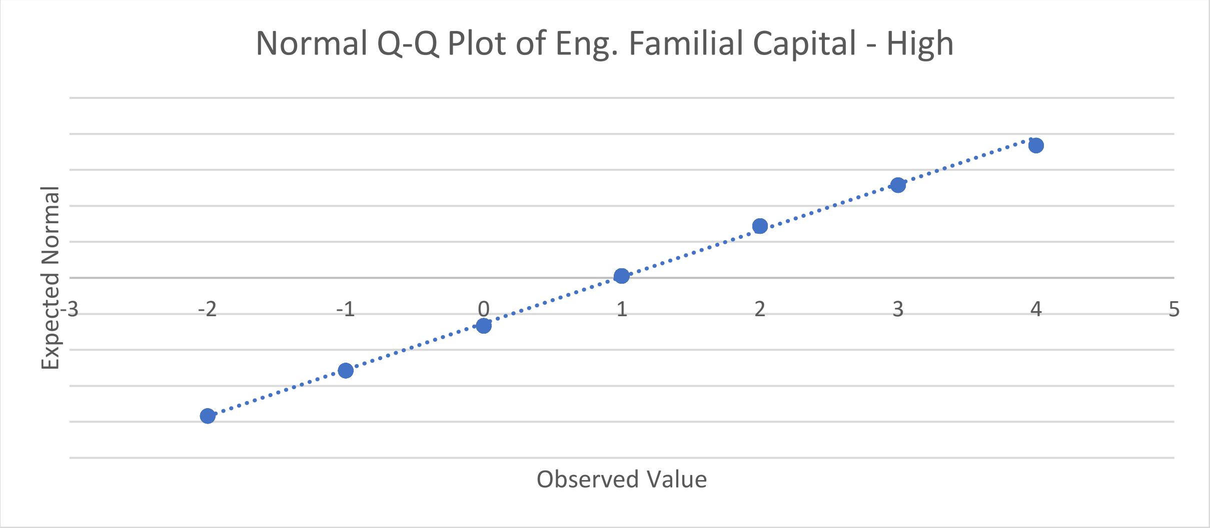
	ENGINEERING_ CAPITAL_ GROUPS	Cases					
		Valid		Missing		Total	
		N	Percent	N	Percent	N	Percent
Eng. Familial Capital	Low	154	88.0%	21	12.0%	175	100.0%
	Medium	638	97.3%	18	2.7%	656	100.0%
	High	90	100.0%	0	0.0%	90	100.0%

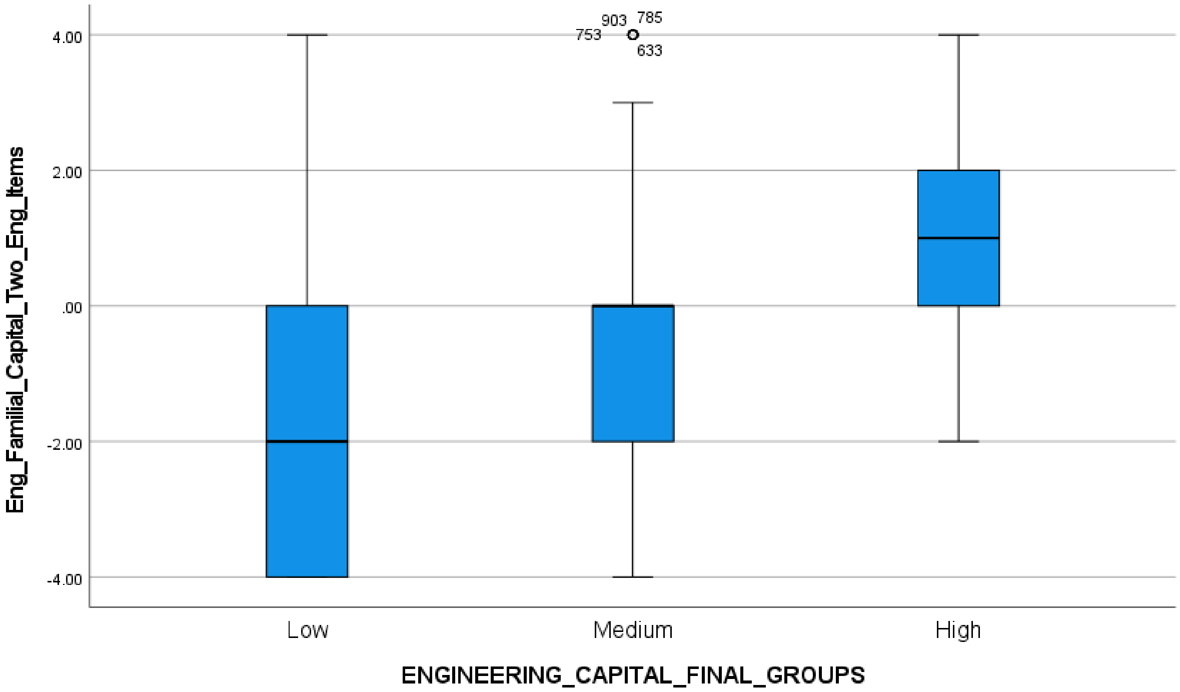
Descriptives

			ENGINEERING_CAPITAL _GROUPS					
			Low		Medium		High	
			Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error
Eng. Familial Capital	Mean		-2.0779	.16391	-.5031	.06782	.9778	.15072
	95% Confidence Interval for Mean	Lower Bound	-2.4018		-.6363		.6783	
		Upper Bound	-1.7541		-.3699		1.2773	
	5% Trimmed Mean		-2.2431		-.5019		.9691	
	Median		-2.0000		.0000		1.0000	
	Variance		4.138		2.935		2.044	
	Std. Deviation		2.03413		1.71314		1.42984	
	Minimum		-4.00		-4.00		-2.00	
	Maximum		4.00		4.00		4.00	
	Range		8.00		8.00		6.00	
	Interquartile Range		4.00		2.00		2.00	
	Skewness		.777	.195	-.065	.097	.087	.254
	Kurtosis		-.132	.389	-.084	.193	-.161	.503


Normal Q-Q Plot of Eng. Familial Capital - Low
Expected Normal
-5
-4
-3
-2
-1
0
1
2
3
4
5
Observed Value


Normal Q-Q Plot of Eng. Familial Capital - Medium
Expected Normal
-5
-4
-3
-2
-1
0
1
2
3
4
5
Observed Value


Normal Q-Q Plot of Eng. Familial Capital - High
Expected Normal
-3
-2
-1
0
1
2
3
4
5
Observed Value


903
785
753
633
4.00
2.00
.00
-2.00
-4.00
Eng_Familial_Capital_Two_Eng_Items
Low
Medium
High
ENGINEERING_CAPITAL_FINAL_GROUPS

A one-way Welch's ANOVA was adopted to determine whether engineering familial capital scores differed between groups based on engineering capital. A total of 882 participants were classified into three groups based on engineering capital scores: Low (N=154), Medium (N=638), and High (N=90). Engineering familial capital scores were found to statistically differ (F(2, 200.623) = 94.038, p<0.001, ETA^2=0.174). Games-Howell post-hoc testing revealed significant differences at all levels between the Low (M=-2.08, SD=2.04), Medium (M=-0.50, SD=1.71) and High (M=0.98, SD=1.43) groups. The ETA^2 size of 0.174 indicates a strong effect of engineering capital in shaping engineering familial capital scores.

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound
Low		154	-2.0779	2.03413	.16391	-2.4018	-1.7541
Medium		638	-.5031	1.71314	.06782	-.6363	-.3699
High		90	.9778	1.42984	.15072	.6783	1.2773
Total		882	-.6270	1.92076	.06468	-.7539	-.5000
Model	Fixed Effects			1.74759	.05884	-.7425	-.5115
	Random Effects				.90816	-4.5345	3.2805

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Eng. Familial Capital	Based on Mean	11.601	2	879	<.001
	Based on Median	9.895	2	879	<.001
	Based on Median and with adjusted df	9.895	2	864.638	<.001
	Based on trimmed mean	12.040	2	879	<.001

ANOVA

Eng_Familial_Capital

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	565.764	2	282.882	92.625	<.001
Within Groups	2684.514	879	3.054		
Total	3250.278	881			

ANOVA Effect Sizes[a]

		Point Estimate	95% Confidence Interval	
			Lower	Upper
Eng_Familial_Capital	Eta-squared	.174	.131	.217
	Epsilon-squared	.172	.129	.215
	Omega-squared Fixed-effect	.172	.128	.215
	Omega-squared Random-effect	.094	.069	.120

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

Robust Tests of Equality of Means

Eng_Familial_Capital

	Statistic[a]	df1	df2	Sig.
Welch	94.038	2	200.623	<.001
Brown-Forsythe	93.315	2	319.268	<.001

a. Asymptotically F distributed.

Multiple Comparisons

Dependent Variable: Eng_Familial_Capital_Two_Eng_Items

	(I) ENG. CAPITAL GROUPS	(J) ENG. CAPITAL GROUPS	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Games-Howell	Low	Medium	-1.57479*	.17739	<.001	-1.9935	-1.1560
		High	-3.05570*	.22267	<.001	-3.5809	-2.5305
	Medium	Low	1.57479*	.17739	<.001	1.1560	1.9935
		High	-1.48091*	.16528	<.001	-1.8728	-1.0890
	High	Low	3.05570*	.22267	<.001	2.5305	3.5809
		Medium	1.48091*	.16528	<.001	1.0890	1.8728

*. The mean difference is significant at the 0.05 level.

One-Way ANOVA: Linguistic Capital

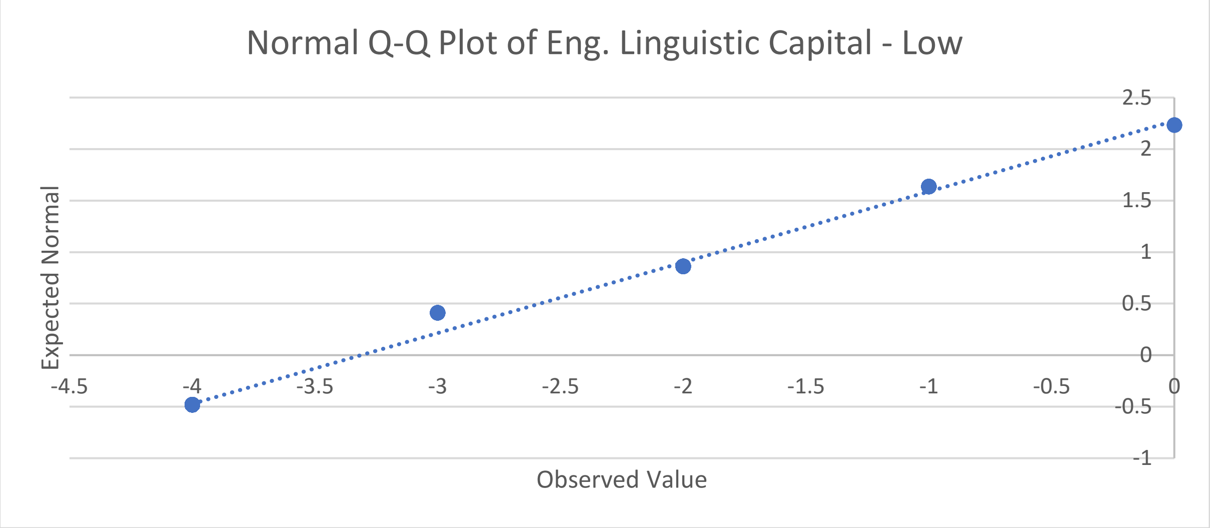
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be largely normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1. The assumptions underpinning this test were met approving its use.

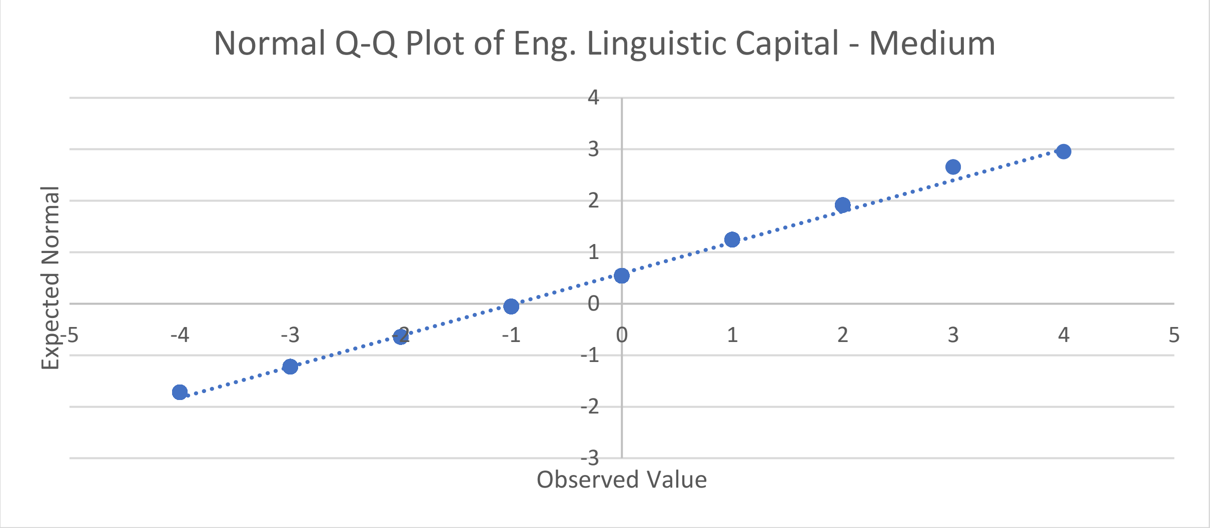
Case Processing Summary

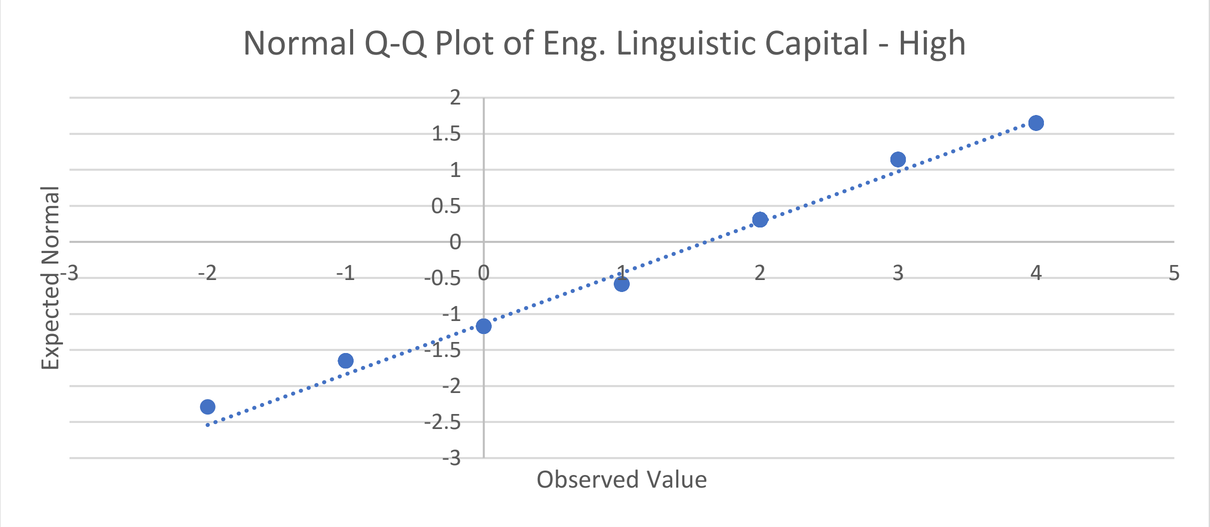
		Cases					
	ENGINEERING CAPITAL GROUPS	Valid		Missing		Total	
		N	Percent	N	Percent	N	Percent
Eng. Linguistic Capital	Low	156	89.1%	19	10.9%	175	100.0%
	Medium	642	97.9%	14	2.1%	656	100.0%
	High	90	100.0%	0	0.0%	90	100.0%

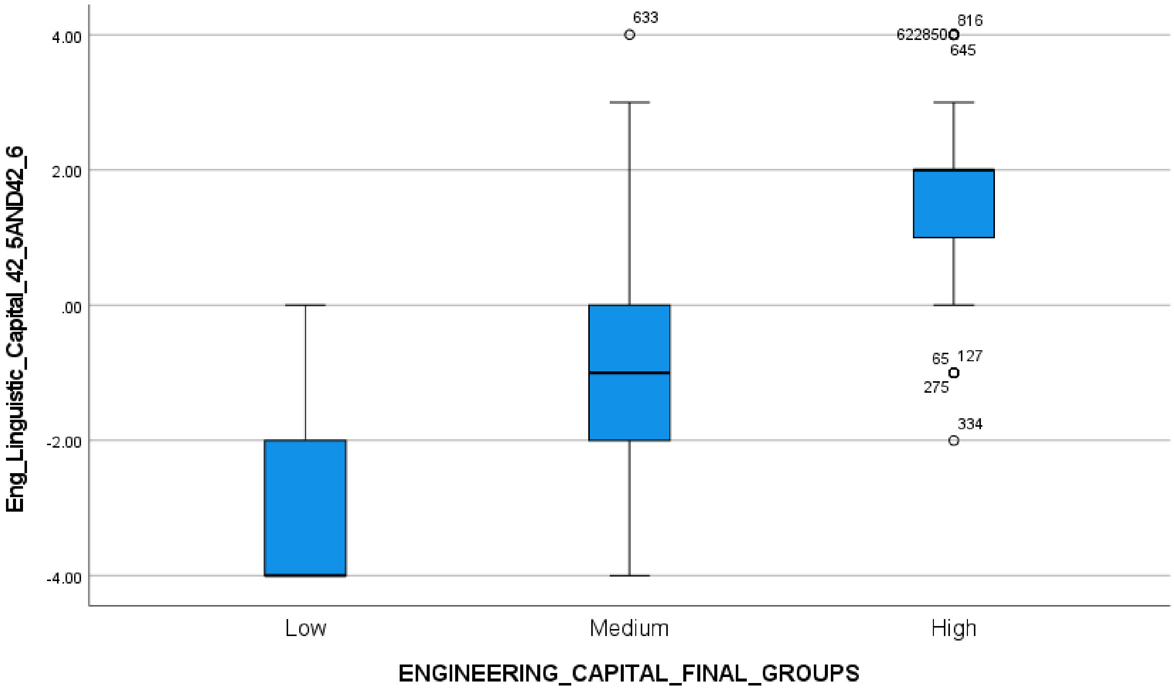
Descriptives

			ENGINEERING CAPITAL GROUPS					
			Low		Medium		High	
			Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error
Eng. Linguistic Capital	Mean		-3.2244	.08844	-.9657	.06132	1.6000	.13389
	95% Confidence Interval for Mean	Lower Bound	-3.3991		-1.0861		1.3340	
		Upper Bound	-3.0496		-.8453		1.8660	
	5% Trimmed Mean		-3.3262		-.9669		1.6235	
	Median		-4.0000		-1.0000		2.0000	
	Variance		1.220		2.414		1.613	
	Std. Deviation		1.10467		1.55364		1.27023	
	Minimum		-4.00		-4.00		-2.00	
	Maximum		.00		4.00		4.00	
	Range		4.00		8.00		6.00	
	Interquartile Range		2.00		2.00		1.00	
	Skewness		1.067	.194	-.120	.096	-.314	.254
	Kurtosis		-.082	.386	-.353	.193	.499	.503


Normal Q-Q Plot of Eng. Linguistic Capital - Low
Expected Normal
Observed Value
2.5
2
1.5
1
0.5
0
-0.5
-1
-4.5
-4
-3.5
-3
-2.5
-2
-1.5
-1
-0.5
0


Normal Q-Q Plot of Eng. Linguistic Capital - Medium
Expected Normal
Observed Value
4
3
2
1
0
-1
-2
-3
-5
-4
-3
-2
-1
0
1
2
3
4
5


Normal Q-Q Plot of Eng. Linguistic Capital - High
Expected Normal
Observed Value
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
-3
-2
-1
0
1
2
3
4
5


Eng_Linguistic_Capital_42_5AND42_6
4.00
2.00
.00
-2.00
-4.00
633
816
622850
645
65
127
275
334
Low
Medium
High
ENGINEERING_CAPITAL_FINAL_GROUPS

A one-way Welch's ANOVA was adopted to determine whether engineering linguistic capital scores differed between groups based on engineering capital. A total of 888 participants were classified into three groups based on engineering capital scores: Low (N=156), Medium (N=642), and High (N=90). Engineering linguistic capital scores were found to statistically differ (F(2, 218.842) = 484.613, p<0.001, ETA^2=0.422). Games-Howell post-hoc testing revealed significant differences at all levels between the Low (M=-3.22, SD=1.10), Medium (M=-0.97, SD=1.55) and High (M=1.60, SD=1.27) groups. The ETA^2 size of 0.422 indicates a strong effect of engineering capital in shaping engineering linguistic capital scores.

Descriptives

Eng_Linguistic_Capital

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum	Between-Component Variance
						Lower Bound	Upper Bound			
Low		156	-3.2244	1.10467	.08844	-3.3991	-3.0496	-4.00	.00	
Medium		642	-.9657	1.55364	.06132	-1.0861	-.8453	-4.00	4.00	
High		90	1.6000	1.27023	.13389	1.3340	1.8660	-2.00	4.00	
Total		888	-1.1025	1.91466	.06425	-1.2286	-.9764	-4.00	4.00	
Model	Fixed Effects			1.45749	.04891	-1.1985	-1.0065			
	Random Effects				1.41172	-7.1766	4.9717			3.53046

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Eng_Linguistic_Capital	Based on Mean	9.259	2	885	<.001
	Based on Median	17.546	2	885	<.001
	Based on Median and with adjusted df	17.546	2	867.633	<.001
	Based on trimmed mean	10.352	2	885	<.001

ANOVA

Eng_Linguistic_Capital

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1371.681	2	685.841	322.857	<.001
Within Groups	1879.994	885	2.124		
Total	3251.675	887			

ANOVA Effect Sizes[a]

		Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
Eng_Linguistic_Capital	Eta-squared	.422	.375	.463
	Epsilon-squared	.421	.374	.462
	Omega-squared Fixed-effect	.420	.374	.462
	Omega-squared Random-effect	.266	.230	.300

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

Robust Tests of Equality of Means

Eng_Linguistic_Capital

	Statistic[a]	df1	df2	Sig.
Welch	484.613	2	218.842	<.001
Brown-Forsythe	438.998	2	316.485	<.001

a. Asymptotically F distributed.

Multiple Comparisons

Dependent Variable: Eng_Linguistic_Capital

	Eng. Cap. Groups.	Eng. Cap. Groups.	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Games-Howell	Low	Medium	-2.25863*	.10762	<.001	-2.5120	-2.0052
		High	-4.82436*	.16047	<.001	-5.2039	-4.4449
	Medium	Low	2.25863*	.10762	<.001	2.0052	2.5120
		High	-2.56573*	.14727	<.001	-2.9149	-2.2166
	High	Low	4.82436*	.16047	<.001	4.4449	5.2039
		Medium	2.56573*	.14727	<.001	2.2166	2.9149

*. The mean difference is significant at the 0.05 level.

One-Way ANOVA: Engineering Engagement

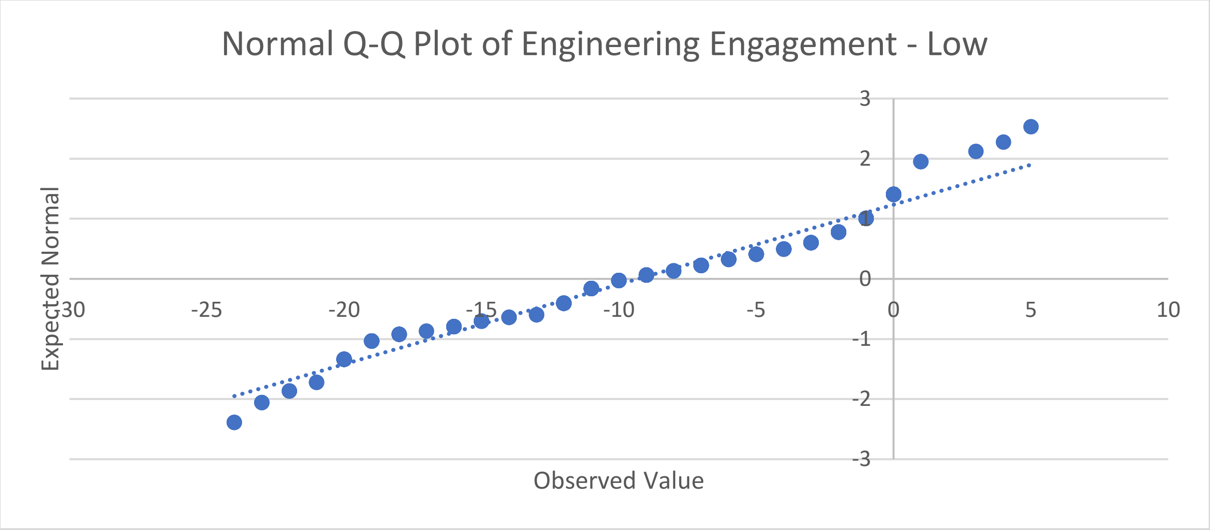
An Explore function was utilised to test the statistical assumptions underpinning the adoption of this test. Outliers and skewness/kurtosis were examined. A number of small outliers were identified, however examination of the 5% trimmed means (means calculated without the highest and lowest 5% of scores) highlighted very little change in means demonstrating a minimal impact of these small outliers. The data was also deemed to be largely normally distributed with a robust Normal Q-Q plot and skewness and kurtosis values within the acceptable range of -1 to 1. The assumptions underpinning this test were met approving its use.

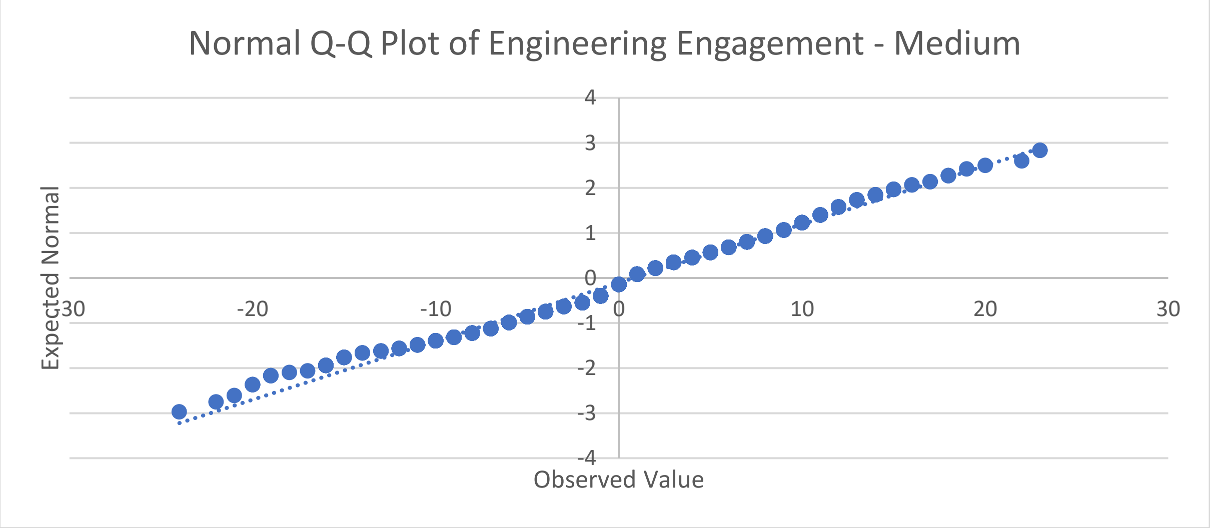
Case Processing Summary

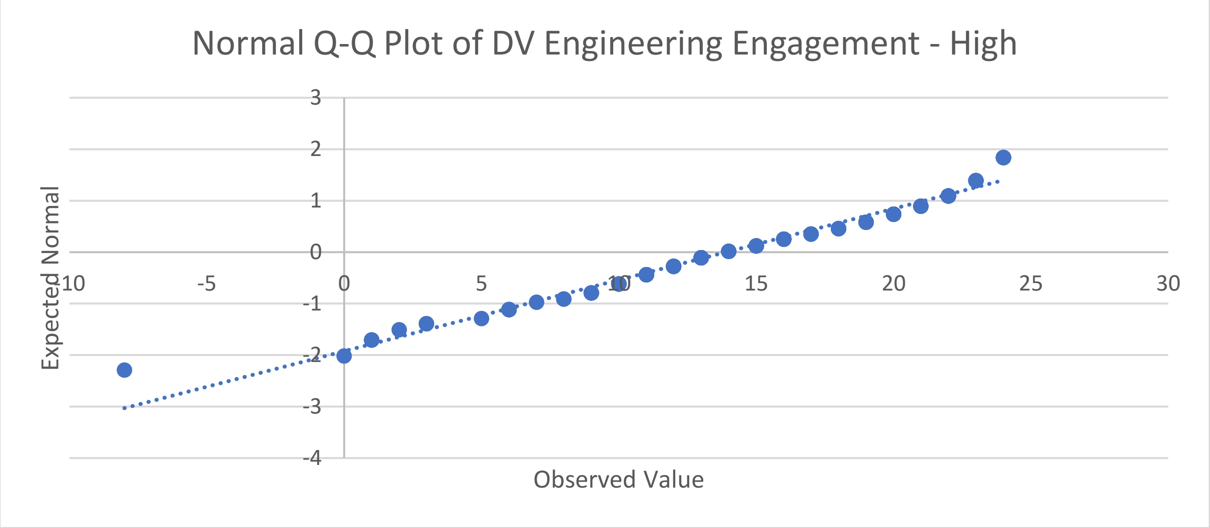
		Cases					
	ENGINEERING CAPITAL GROUPS	Valid		Missing		Total	
		N	Percent	N	Percent	N	Percent
Eng. Engagement	Low	175	100.0%	0	0.0%	175	100.0%
	Medium	656	100.0%	0	0.0%	656	100.0%
	High	90	100.0%	0	0.0%	90	100.0%

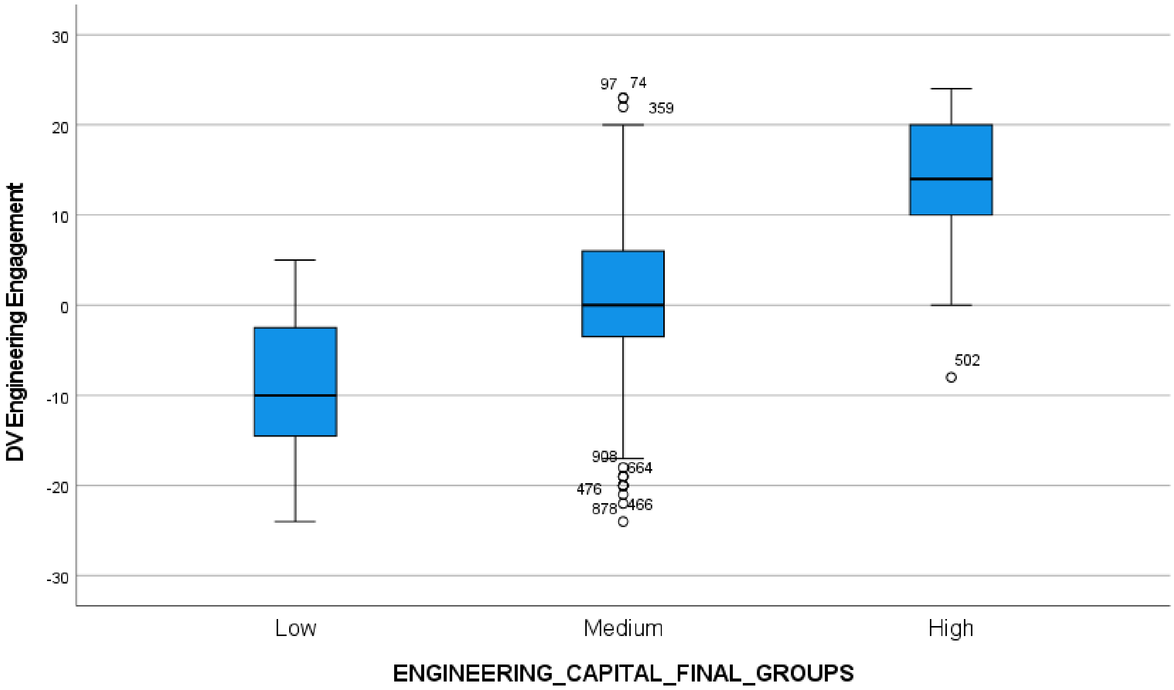
Descriptives

			ENGINEERING CAPITAL GROUPS					
			Low		Medium		High	
			Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error
Eng. Engagement	Mean		-9.31	.542	.81	.296	13.88	.716
	95% Confidence Interval for Mean	Lower Bound	-10.38		.23		12.45	
		Upper Bound	-8.25		1.39		15.30	
	5% Trimmed Mean		-9.20		.98		14.15	
	Median		-10.00		.00		14.00	
	Variance		51.343		57.446		46.198	
	Std. Deviation		7.165		7.579		6.797	
	Minimum		-24		-24		-8	
	Maximum		5		23		24	
	Range		29		47		32	
	Interquartile Range		13		10		10	
	Skewness		-.191	.184	-.279	.095	-.513	.254
	Kurtosis		-1.035	.365	.476	.191	.028	.503


Normal Q-Q Plot of Engineering Engagement - Low
Expected Normal
Observed Value
3
2
1
0
-1
-2
-3
-30
-25
-20
-15
-10
-5
0
5
10


Normal Q-Q Plot of Engineering Engagement - Medium
Expected Normal
Observed Value
4
3
2
1
0
-1
-2
-3
-4
-30
-20
-10
0
10
20
30


Normal Q-Q Plot of DV Engineering Engagement - High
Expected Normal
Observed Value
3
2
1
0
-1
-2
-3
-4
-10
-5
0
5
10
15
20
25
30


30
20
10
0
-10
-20
-30
DV Engineering Engagement
97
74
359
908
664
476
878
466
502
Low
Medium
High
ENGINEERING_CAPITAL_FINAL_GROUPS

A one-way ANOVA was adopted to determine whether engineering engagement scores differed between groups based on engineering capital. A total of 921 participants were classified into three groups based on engineering capital scores: Low (N=175), Medium (N=656), and High (N=90). Engineering engagement scores were found to statistically differ (F(2, 918) = 298.204, p<0.001, ETA^2=0.394). Tukey post-hoc testing revealed significant differences at all levels between the Low (M=-9.31, SD=7.17), Medium (M=0.81, SD=7.58) and High (M=13.88, SD=6.80) groups. The ETA^2 size of 0.394 indicates a strong effect of engineering capital in shaping engineering engagement scores.

Descriptives

DV Engineering Engagement

					95% Confidence Interval for Mean			
	N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound	Minimum	Maximum
Low	175	-9.31	7.165	.542	-10.38	-8.25	-24	5
Medium	656	.81	7.579	.296	.23	1.39	-24	23
High	90	13.88	6.797	.716	12.45	15.30	-8	24
Total	921	.16	9.532	.314	-.45	.78	-24	24

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
DV Engineering Engagement	Based on Mean	.547	2	918	.579
	Based on Median	.521	2	918	.594
	Based on Median and with adjusted df	.521	2	879.394	.594
	Based on trimmed mean	.543	2	918	.581

ANOVA

DV Engineering Engagement

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	32921.019	2	16460.509	298.204	<.001
Within Groups	50672.551	918	55.199		
Total	83593.570	920			

ANOVA Effect Sizes[a]

		Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
DV Engineering Engagement	Eta-squared	.394	.347	.435
	Epsilon-squared	.393	.346	.434
	Omega-squared Fixed-effect	.392	.346	.434
	Omega-squared Random-effect	.244	.209	.277

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

Multiple Comparisons

Dependent Variable: DV Engineering Engagement

Tukey HSD

(I) ENGINEERING CAPITAL GROUPS	(J) ENGINEERING CAPITAL GROUPS	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Low	Medium	-10.124*	.632	<.001	-11.61	-8.64
	High	-23.192*	.964	<.001	-25.45	-20.93
Medium	Low	10.124*	.632	<.001	8.64	11.61
	High	-13.068*	.835	<.001	-15.03	-11.11
High	Low	23.192*	.964	<.001	20.93	25.45
	Medium	13.068*	.835	<.001	11.11	15.03

*. The mean difference is significant at the 0.05 level.