Human-centred Persona Driven Personalization in Business Data Analytics

CHRISTOS AMYROTOS, InSPIRE Center, School of Sciences, UCLan Cyprus, Cyprus
PANAYIOTIS ANDREOU, InSPIRE Center, School of Sciences, UCLan Cyprus, Cyprus
PANAGIOTIS GERMANAKOS*, UX S/4HANA, Product Engineering, IEG, SAP SE, Germany

The modern business environment is empowered by the abundant availability of data and plethora of sophisticated data analysis tools to identify and quickly address market needs. While these tools have evolved significantly during the last years, offering trailblazing data exploration experiences with stunning multi-modal visualizations, they mistreat the importance of individualized, user-centred delivery of information/insights. As a result, users may require much more effort and time to reach decisions that have implications on both the short-term and long-term success of sustainability of an organization. This paper highlights the need for user-centred/persona-driven data exploration through adaptive data visualizations and personalized support to an end-to-end business process. It proposes an extended human-centred persona and discusses preliminary exploratory results in relation to the formulation of the contextual characteristics of a business environment, i.e., business tasks, visualizations and data.

CCS Concepts: • **Human-centered computing**; • **Information systems**; • **Applied computing**;

Additional Key Words and Phrases: Adaptation, Personalization, Human Factors, User Modeling, Artificial Intelligence, Business Analytics, Data Visualizations

ACM Reference Format:
Christos Amyrotos, Panayiotis Andreou, and Panagiotis Germanakos. 2021. Human-centred Persona Driven Personalization in Business Data Analytics. In *Adjunct Proceedings of the 29th ACM Conference on User Modeling, Adaptation and Personalization (UMAP '21 Adjunct), June 21–25, 2021, Utrecht, Netherlands.* ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3450614.3462241

1 INTRODUCTION

Nowadays, business users have access to a range of data from a variety of sources to complete their assigned responsibilities and tasks. These data may be generated from Business Intelligence and Data Analytics Platforms (such as SAS Visual Analytics[1], IBM Analytics[2], Microsoft Power BI[3], SAP Business Intelligence Platform[4], Tableau Business Intelligence and Analytics[5], etc.), that offer the same functionality (e.g., visualization types, content and interaction paradigms) to all users. Although some visualizations provided by those platforms/tools might be considered more usable/understandable than others [20], usually their recipients (e.g., data analysts) are overloaded from the large amount of visual information they have to process, since in principle such platforms do not consider in the core of their solutions the end-users' individual differences. Additionally, algorithms employed by such platforms are mostly maintained by adhering to static

*Also affiliated with the InSPIRE Center, Cyprus
[1]https://www.sas.com
[2]www.ibm.com/analytics/us/en/technology/products/cognos-analytics/
[3]https://powerbi.microsoft.com/en-us/
[4]https://www.sap.com/products/bi-platform.html
[5]http://www.tableau.com

monolithic role-based specifications or user needs and requirements, that comply to definitions that are formulated having the power users (e.g., expert data analysts) in mind. For this reason, it becomes even easier for users to lose focus in terms of navigation, while also they might not be able to take fast and accurate decisions when performing their expected business activities [4, 16]. This paper argues that the complex nature of many business data visualizations, objectives, tasks and large business datasets makes it essential to include human intelligence in the business data analysis and visualization process at an early stage. This inclusion will help enrich tools and applications with adaptation techniques and new possibilities for interaction that will consider human-centred personas of business users in every business process or computational procedure. Our consideration of human intelligence as means for adaptation is fueled by the influence and effects of human factors in tasks that entail data or information visualizations. Such effects have been demonstrated in numerous application fields during the last decade, including educational and navigation contents, public facing applications and information retrieval or health datasets. Indicatively, numerous research works have found associations with respect to users' cognitive abilities like perceptual speed (involving visual perception and scanning), workload perception on search behavior, and data visualization types like bar graphs and radar graphs in relation to users' performance [5, 7, 28]; working memory, preference and tasks when users interact with various data visualizations – as a form of integrated objects that contain colours, orientation, and shape – and elements (visual or textual) [17, 26, 29]; spatial ability and visualization comprehension, investigating compatibility of the verbal metaphors with visual metaphors [32, 35]; cognitive styles, like Field Dependent-Independent, and impact on interactions with various information visualizations in relation to individual aid choices and preferences [27]; personality influence on performance during visualization tasks [7, 14]; emotion-triggered (e.g., boredom and frustration) adaptation methods effective for visualization systems [8].

Nevertheless, although significant effects have been observed in user-data visualization interactions by multiple works and in a variety of application domains, these ideas have rarely been applied, to our knowledge, to the business sector despite the encouraging findings [23]. Henceforth, the vision of this research work is to provide a preliminary step towards addressing this gap for enabling human-centred adaptive data visualizations that will facilitate efficient exploration and analysis of complex and multivariate business datasets, thus, enabling more effective decision making on critical business tasks. This paper aims: (a) to build upon prior research on the impact of individual differences on data visualizations, for proposing an innovative theoretical human-centred model in the business data analytics domain, and (b) to study and explore the direct object of investigation, i.e., business tasks, visualizations and data, that constitute the contextual frame of execution for a business user. In this respect, we present the results of a preliminary exploratory study with 59 business users (data analysts), in an attempt to create a first understanding of the similarities and differences between current approaches and possible approaches that are compatible with the business domain by extracting the business context requirements i.e., characteristics for supporting decisions when crafting adaptive and personalized interventions to be used in business data analytics.

2 OVERVIEWING A HUMAN-CENTRED MODEL FOR PERSONALIZATION IN BUSINESS DATA ANALYTICS

A persona in the business sector constitutes a fictional representation of a business role, e.g., Project Manager, Business Analyst, Data Analyst, that might represent one or more end-users, and consists of characteristics like demographics, goals, responsibilities, wishes, needs, painpoints, etc., providing some good insights for the end-users that a product is designed for [15]. However, the demanding nature of business processes, data and visualizations require adaptive and personalized solutions that bring individual differences in the center of attention to build human-centred personas

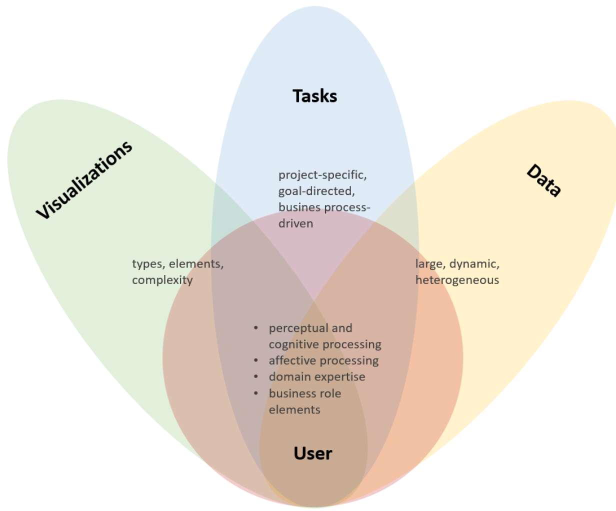

Fig. 1. Proposed Human-centred Business Persona

that will guide the respective interactions. This paper considers a persona as the core component of an adaptive data analytics platform, and proposes enriching its current definition with more intrinsic values of users extending its scope and sophistication. It mainly focuses in theories of user's individual differences in information and affective processing, and domain expertise, for providing adaptive and personalized solutions in the business context and information discovery.

The following sections overview the selected human factors of the proposed theoretical model (see Figure 1), and guided by findings of the related literature argues on the expected impact when end-users interact with business data visualizations. Main purpose is not to compose an exhaustive theoretical model, but rather to employ those human aspects that together with the business contextual characteristics (i.e., role, expertise, business processes/tasks and data) would be able to jointly facilitate more comprehensive persona composition, apt adaptive interventions, personalization conditions and explanations during the visual data exploration process.

2.1 User

The business end-user is the focal point in the definition of the extended persona, referring on one hand to the understanding of the business roles, nature and their contexts of functioning, and on the other hand to the identification of the intrinsic human factors that play the most significant role during their engagement with the data visualizations. Considering the various theories and models of individual differences in the literature, the following factors have been promoted as more applicable for the scope of this research work (in relation to specific business settings and actions):

The ***perceptual and cognitive processing characteristics***, are mainly distinguished in users': (a) high-level information processes, like cognitive styles [34] that have a direct impact on the type (textual or imagery) of the content and may influence preferences and decision making in data visualization scenarios [27], and (b) elementary cognitive processes (i.e., working memory, controlled attention and speed of processing), that have an effect on the complexity of the content regarding users' task performance, overall efficiency and cognitive control of visual information [26], or problem solving and comprehension during the interaction process. Regarding individual characteristics that affect the perception of visualizations, models that relate to graphical or visual (numeric) literacy or guidance (i.e., reading between and beyond data to understand abstract, data-driven associations – [11]) have been qualified expecting that high levels of visual literacy will impact users' reasoning with visual representations making more elaborate inferences (extracting information from more complex visualizations) as opposed to those with low [22]. Furthermore, emphasis will be placed upon end-users' personality [13] (and Need for Cognition as a variable of personality indicating the extend to which an individual may engage into effortful cognitive activities [6]), as influential human traits of the perceptual process, motivation and behaviour. It is expected that they will affect users during the visual interaction process with respect to accuracy (including error rates), search and performance when executing tasks, problem-solving approaches and skills [14, 21].

The ***affective processing*** (or affective states) guides behaviour and emotions, as behavioural output of the process [33], and refers to a range of feelings that people experience, including discrete emotions, moods and traits (such as positive and negative affectivity). It may be at some extent deduced into two basic constructs, i.e., Emotional Arousal and Emotion Regulation, influencing people's performance, judgement and decision making process while interacting with data visualizations [19]. For example, users with a negative affective state require environmental enhancements to work more efficiently, as their emotional needs alter their behaviour and create different informational and processing demands [19].

The ***domain expertise*** indicates how skillful a user is in the domain (s)he functions and it is associated with graph understanding, accuracy and performance (time spent) in relation to visual tasks complexity (e.g., less experienced individuals may spend more time in information retrieval and comparison of sub-stages) [1, 10]. Also, it affects preference, satisfaction and the capability of being familiarized or switching between graphs to obtain information, e.g., novice users have greater difficulties of using different visualization types [30].

The ***business role characteristics*** refer to more "traditional" persona elements defined from a person's or an entity's business responsibilities, objectives and tasks. It may include, personal, professional or technical information [31], competencies, expectations, needs, feelings, painpoints, usually associated to specific activities that are tightly linked to one (or more) business processes within an organization. This paper builds on the premise that data visualizations should be coupled with the goals and requirements of each business role and consider the variability of tasks, level of knowledge, constraints, etc., for conveying the adequate information, when and how it is needed, and on the expected breadth and depth that could facilitate fast and accurate decision making [3].

2.2 Tasks, Data and Visualizations

Partially, the ***business tasks*** formulate the context of execution (sequence of project-specific actions) and interaction for an end-user (or persona), relating to situation-specific scenarios, requirements and constraints depending on the line of business. Tasks may be regarded as a solid point of reference for designing usable interactive data visualizations, but they usually comply with business data models and processes characterized by increased complexity, making the analysis and understanding of information by various non-power users (e.g., data analysts, business analysts) challenging, time consuming, costly, if not many times impossible.

Such information resonates in various ***data*** sources found in different locations, are of different types, have different data characteristics (e.g., criticality, real-time, historical), and are connected to complex (customer-specific) data models and business processes. Hence, efficient semantic mapping among features is critical, so that integrated data analysis is possible and comparable through intuitive data visualizations. As such, structured learning and graphical models like probabilistic dependency networks, probabilistic decision trees, Bayesian networks and Markov Random Fields, are becoming popular business data mining tools helping to deal with open case-based data challenges like scalability, uncertainty and data quality, dynamicity, heterogeneity, etc. [9] Therefore, it is widely accepted that the increasingly large amount of data requires novel, efficient, and user-friendly data visualization solutions.

As such, handling, analyzing and gaining insights into these large multivariate datasets through interactive and explainable data ***visualizations*** is one of the major challenges of our days and this work. Main goal is to specify the properties and structure of the content of data visualizations and exploration support. Subsequently, a further identification and characterization of parameters that will enable the adaptation based on the human-centred model will take place. Currently, there are different types of visualizations (e.g., bar, column, line and area charts, radar graphs, plots and tables) which communicate information and meaning out of data, always in relation to the scope and the needs of a task. Once data visualization content is defined and semantically augmented, various adaptation and personalization mechanics may offer dynamic hierarchical structure and content presentation adjustments, provision of real-time navigation support and event-driven explanations, flexible user control and cooperation, etc.

Given the users' diversified requirements, needs and perceptual preferences as well as the size, diversity and processing overhead of big business data sets, it is expected that proposed human-centred persona will yield flexible best-fit data visualizations and methods that will support the unique end-users during the end-to-end interaction process. The main challenge is to identify and develop enhanced data representations that will be able to capture the fuzzy human nature and multi-objective tasks in terms of providing information in different modalities, navigation patterns and interaction logic thus allowing for adaptation based on users' cognitive and affective processing abilities, role, expertise and tasks.

3 A USER STUDY FOR EXPLORING THE BUSINESS ANALYTICS CONTEXT

3.1 Motivation and Research Questions

In addition to the users' requirements, needs and complicated human factors/nature, the proposed extension of the persona also made evident the importance of the business context for providing effective adaptations to the business end users. In this respect, the first step is to investigate the contextual building blocks of the business environment like tasks, visualization types and data (see section 2.2), so to crystallize a viewpoint around the expected adaptation and personalization specifications. We formulate the following research questions: ***RQ1***: Which are the most common tasks of the data analyst in the business domain regarding data visualization and exploration, and how do those differ from tasks in other domains? ***RQ2***: What kind of data, visualizations and methods are used for the defined tasks? ***RQ3***: Which are the main challenges and needs of data analysts in the business domain?

3.2 Sampling and Procedure

For this exploration study, we involved business participants that have on average at least 2 years of experience in the field of data analytics, and their interaction with data visualizations is part of their daily job responsibilities. The recruitment was made possible with the support of two collaborator organizations via direct messaging to their end-users; resulting in a total of 59 data analysts. The sample consisted of 28 Male and 31 Female participants, with their ages ranging from 22 to 56 years old (M = 32, SD = 7). All participants were analysts, working on different industry fields such as Retail, Marketing, Advisory Services, Audit and Risk Assessment, while they were of varying expertise levels including managers/directors, executive analysts, senior analysis, junior analysts and data engineering/quality assurance. For capturing their proficiency and experience we analysed the reported educational status (all end-users had achieved higher education), their working experience (ranged from 1 to 25 years (M = 4.3, SD = 6.2)), as well as their Visual Literacy (M = 3.9, SD = 0.7 – captured using the Subjective Graphical Literacy Scale [12]) and Self-Expertise (M = 3.1, SD = 1.3 – obtained through a single 5-point scale self-reporting measure of perceived expertise, i.e., "My level of expertise for the current business role is", where 1 is Novice and 5 is Expert). The Self-Expertise scale was used in conjunction with the participants' working experience in years and their Visual Literacy for further validating and cross verifying the recruited sample's expertise (that was expected to be high for the purposes of this exploratory study). Overall, the above findings suggest that the sample is indeed within the initial expectations and goals of this study. For the execution part, a Web-based environment was created including of a series of questionnaires (i.e., open-ended and likert-scale questions). The study ran in a controlled environment in two sessions with 36 participants in the first and 23 in the second. Each study session was hosted at the premises of each company and was executed sequentially, with a group of 4 to 7 analysts completing the questionnaires at a time, depending on their availability. For every new group of participants a researcher was presenting the overall study goals and an overview of the study tasks. At all times during the study the researcher was also in charge for guiding the participants and for answering any potential questions or even resolving any technical conflicts. The participation was voluntary, adhering to the GDPR rules and regulations [24], while each participant required on average 20-25 minutes for completing the questionnaire corpus. After participants provided their demographics, such as Gender, Age and Educational Status, they responded to a set of open-ended questions, aiming to collect information regarding RQ_1 with respect to typical business tasks they perform while using visualizations (e.g., Exploration, Correlation, Data Preparation) and their frequency, weekly data analysis requests and their working experience. For addressing RQ_2 participants were given: (a) a matrix of check boxes (19 visualization types by 10 task actions) where they had to check a maximum of 3 visualization types that they preferred for completing each type of action e.g., Bar, Pie and Column chart used for performing Comparison, and (b) a number of visualization types where they had to report the complexity of each type on a likert-scale. Finally, for RQ_3 participants had to state the challenges (i.e., painpoints) they face during data exploration (including interaction with data visualizations) for accomplishing their business tasks and wishes for improving their daily operations.

3.3 Analysis and Discussion of the Results

Initially, the use of open ended questions necessitates the extraction and coding of themes for each of the provided answers. Hence, our analysis adhered to the following process: (a) Clean textual responses by removing punctuation, stop words, single letters and unnecessary white space with custom string manipulation functions in Python; (b) generate a document-term matrix; (c) visualize the terms, i.e., words in a word-cloud; (d) manually read answers for formulating different themes and coding specific words into that theme, e.g., if answer contains the words "data" and "cleaning" then code this into a single new term named "DataCleaning"; (e) repeat from step *(c)* until a list of themes and their frequencies for a question are formed. Accordingly, descriptive analyses such as frequency distributions and mean were obtained to characterize the derived data.

Thereupon, regarding ***RQ_1*** (i.e., common business tasks), participants responded as follows: 71% Improve Data Quality, 13% Performance Analysis, 12% Correlation Analysis, 12% Comparison Analysis, 12% Drawing Conclusions and 10% Presentations. Other common answers included, pattern detection, trend or sales analysis and visualizing KPIs. During their business tasks participants reported that they use data visualizations for an average of 2.5 days per week (M = 2.5, SD = 1.5) and 2.5 hours per day (M = 2.5, SD = 1.3), while they handle an average of 3.5 data analysis requests (M = 3.5, SD = 2.6) on a weekly basis. When asked about the frequency of actions performed during their business tasks,

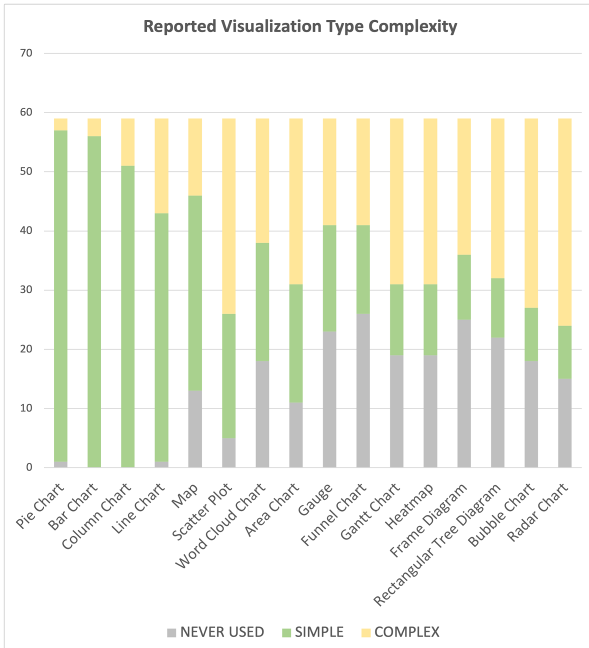

Fig. 2. Reported Visualization Type Complexity

participants responded with Data Preparation, Exploration and Data Communication as the most frequent actions, and with Correlation, Prediction and Classification as the least frequent actions.

The responses of the end-users for $\boldsymbol{RQ_2}$ (i.e., types and complexity of data visualizations, in relation to tasks) show that Pie Charts and Bar Charts (95%), Column Charts (86%) and Line Charts (71%) are considered as simple charts; Radar Charts (59%), Bubble Charts (54%), Gantt Charts and Heatmaps (47%), and Rectangular Tree Diagrams (46%) are considered as complicated charts (taking in consideration also how many people voted those as simple i.e., the scatter plot is considered complex by 33 participants while 21 participants stated that it is instead simple - therefore balancing its complexity level); and Funnel Charts (44%), Frame Diagrams (42%), Gauges (39%) and Rectangular Tree Diagrams (37%) are rated the highest for being "never used". Our results for bar chart and radar graph partially agree with the findings of [28] on visualization ease of use and comprehension, whereby the charts classified as simple are commonly used in various analytic systems and dashboards [18] and thus people are more familiar with them. Figure 2 provides more information on the full data collected regarding visualization type complexity. In addition, regarding the preferred types of visualizations for different types of task actions, the analysis revealed that for all actions (i.e., Comparison, Distribution, Contribution, Correlation, Deviation, Cycles, Composition, Trend and Relationship) participants tended to select visualizations that were considered as simple, with the bar chart to be the most preferred visualization. Figure 3 provides more detailed insights on the visualizations that received the highest preference for a specific task action. Some of the collected results are in line with previous findings [25], e.g., using line charts for correlations.

Lastly, for understating the main challenges and needs of data analysts in the business domain ($\boldsymbol{RQ_3}$), we analyzed the main themes provided in end-users' responses about painpoints and wishes. The major painpoints reported were related to Time Consuming Processes (39%), data related issues such as bad quality of data (41%), data variability (13%), large

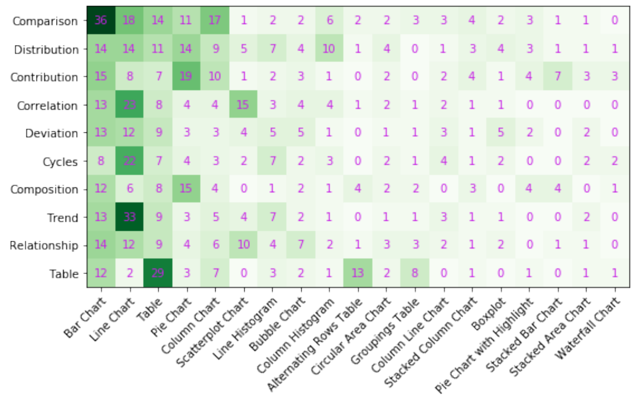

Fig. 3. Visualization Types for Task - Preference

data volumes (19%) and multiple data sources (7%), hardware speed (12%) and poor or not user friendly visualizations (15%). On the other hand, participants' wishes were related to asking for better visualization (more automated) tools (17%), faster processes, i.e., better hardware (22%), reduction of analysis steps (8%), easier data integration (7%) and generally user friendly tools (7%). In relation to RQ_2, the above findings offer a preliminary input on the nature of business data (i.e., large volume/dimensions, multiple data sources and dirty data) being used for the reported tasks in the business domain (also in alignment with the data characteristics in section 2.2).

Interpreting our exploratory findings with respect to adaptation and personalization requirements, at a first sight the business tasks could relate to more generic tasks' definitions and structures [2], or specific data visualization types to be used for more commonly recognized actions [7, 25, 26, 28], applicable across domains. However, a closer look may reveal significant differences that focus primarily upon: (a) the process of data exploration in the business sector encapsulates a thought process (e.g., a sequence of tasks) that is composed of many subsequent tasks that need to be executed so to satisfy a single goal. As opposed to other domains where single visualizations might reflect stand alone tasks, in this case there is a purposeful workflow that needs to be satisfied, where information and consecutive actions are part of a bigger picture (goal) feeding other actions (from the same or different workflows/roles) until a produced logical result. Visual exploration needs to be flexible, conversational, cooperative and interactive to be able to accommodate such composite requirements, triggered by process-driven and not single task-driven end-to-end scenarios; (b) in many cases, one simple business activity of users may be supported from custom-made developments (e.g., using Excel) for the successive execution of steps necessary towards the fulfilment of the primary objective. As a result, single data visualizations might refer to more than one tasks and need to be adjusted or integrated based on a number of diverse factors and tools; and (c) for a single objective a combined knowledge is required from end-users to accomplish a series of tasks, many times with hidden dependencies and implications driven by predefined business workflows. Accordingly, different data-sets and descriptions may feed the same data visualizations, so transparent exploration and intuitive explanations need to capture the breadth, depth and inherent semantic dependencies generated by the data sources.

4 CONCLUSION

While the influence and effect of human factors on visualizations has been widely explored and found significant in various application fields, the business sector to date has failed to inclusively consider them in the modeling and implementation of data analytics solutions. To address this research gap, we proposed a model with specific human factors for the enhancement of current end-user personas detailing how it may extend prior research. We demonstrated preliminary exploration results from a user study of 59 industry data analysts formulating an understanding of the business contextual characteristics (in terms of tasks, visualizations and data) and the requirements for adaptation and personalization. Our exploratory findings solidify our consideration of the business context as a distinctive facet of this application area, revealing the complex nature of business tasks and data as well as the requirement for advanced usable visualization tools, i.e., built with the user in mind rather than solid one-size-fits all or data-driven approaches. We expect that the proposed human-centred business persona will facilitate the data exploration journey by enabling flexible best-fit data visualizations and methods that will support the unique end-users during the end-to-end interaction process.

5 ACKNOWLEDGEMENTS

This research is partially funded by the Cyprus Research and Innovation Foundation under the projects IDEALVis (EXCELLENCE/0918/0366) and RABIT (START-UPS/0618/0053) and the European Union under the project SLICES-DS (No.951850).

REFERENCES

[1] Bryce Allen. 2000. Individual differences and the conundrums of user-centered design: Two experiments. *Journal of the american society for information science* 51, 6 (2000), 508–520.

[2] Robert Amar, James Eagan, and John Stasko. 2005. Low-level components of analytic activity in information visualization. In *IEEE Symposium on Information Visualization, 2005. INFOVIS 2005.* IEEE, 111–117.

[3] Christos Amyrotos, Panayiotis Andreou, and Panagiotis Germanakos. 2021. Adaptive Business Data Visualizations and Exploration: A Human-centred Perspective. In *Proceedings of the 5th HUMANIZE Workshop.*

[4] Georges-Pierre Bonneau, Hans-Christian Hege, Chris R Johnson, Manuel M Oliveira, Kristin Potter, Penny Rheingans, and Thomas Schultz. 2014. Overview and state-of-the-art of uncertainty visualization. In *Scientific Visualization.* Springer, 3–27.

[5] Kathy Brennan, Diane Kelly, and Jaime Arguello. 2014. The effect of cognitive abilities on information search for tasks of varying levels of complexity. In *proceedings of the 5th information interaction in context symposium.* 165–174.

[6] John T Cacioppo and Richard E Petty. 1982. The need for cognition. *Journal of personality and social psychology* 42, 1 (1982), 116.

[7] Giuseppe Carenini, Cristina Conati, Enamul Hoque, Ben Steichen, Dereck Toker, and James Enns. 2014. Highlighting interventions and user differences: Informing adaptive information visualization support. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.* 1835–1844.

[8] Daniel Cernea, Achim Ebert, and Andreas Kerren. 2013. A Study of Emotion-triggered Adaptation Methods for Interactive Visualization.. In *UMAP Workshops.*

[9] Hsinchun Chen, Roger HL Chiang, and Veda C Storey. 2012. Business intelligence and analytics: From big data to big impact. *MIS quarterly* (2012), 1165–1188.

[10] Stuart E Dreyfus and Hubert L Dreyfus. 1980. *A five-stage model of the mental activities involved in directed skill acquisition.* Technical Report. California Univ Berkeley Operations Research Center.

[11] Susan N Friel, Frances R Curcio, and George W Bright. 2001. Making sense of graphs: Critical factors influencing comprehension and instructional implications. *Journal for Research in mathematics Education* 32, 2 (2001), 124–158.

[12] Rocio Garcia-Retamero, Edward T Cokely, Saima Ghazal, and Alexander Joeris. 2016. Measuring graph literacy without a test: A brief subjective assessment. *Medical Decision Making* 36, 7 (2016), 854–867.

[13] Lewis R Goldberg. 1990. An alternative" description of personality": the big-five factor structure. *Journal of personality and social psychology* 59, 6 (1990), 1216.

[14] Tear Marie Green and Brian Fisher. 2010. Towards the personal equation of interaction: The impact of personality factors on visual analytics interface interaction. In *2010 IEEE Symposium on Visual Analytics Science and Technology.* IEEE, 203–210.

[15] Tharon W Howard. 2015. Are personas really usable? *Communication Design Quarterly Review* 3, 2 (2015), 20–26.

[16] Christoph Kinkeldey, Alan M MacEachren, Maria Riveiro, and Jochen Schiewe. 2017. Evaluating the effect of visually represented geodata uncertainty on decision-making: systematic review, lessons learned, and recommendations. *Cartography and Geographic Information Science* 44, 1 (2017), 1–21.

[17] Sébastien Lallé, Cristina Conati, and Giuseppe Carenini. 2017. Impact of individual differences on user experience with a real-world visualization interface for public engagement. In *Proceedings of the 25th Conference on User Modeling, Adaptation and Personalization.* 369–370.

[18] Sukwon Lee, Sung-Hee Kim, and Bum Chul Kwon. 2017. VLAT: Development of a Visualization Literacy Assessment Test. *IEEE Transactions on Visualization and Computer Graphics* 23, 1 (Jan. 2017), 551–560. https://doi.org/10.1109/TVCG.2016.2598920

[19] Zacharias Lekkas, Nikos Tsianos, Panagiotis Germanakos, Constantinos Mourlas, and George Samaras. 2009. The role of affect in personalized learning. In *2009 Ninth IEEE International Conference on Advanced Learning Technologies*. IEEE, 629–633.

[20] Shixia Liu, Weiwei Cui, Yingcai Wu, and Mengchen Liu. 2014. A survey on information visualization: recent advances and challenges. *The Visual Computer* 30, 12 (2014), 1373–1393.

[21] Zhengliang Liu, R Jordan Crouser, and Alvitta Ottley. 2020. Survey on individual differences in visualization. In *Computer Graphics Forum*, Vol. 39. Wiley Online Library, 693–712.

[22] Yasmina Okan, Rocio Garcia-Retamero, Edward T Cokely, and Antonio Maldonado. 2012. Individual differences in graph literacy: Overcoming denominator neglect in risk comprehension. *Journal of Behavioral Decision Making* 25, 4 (2012), 390–401.

[23] Tristan Poetzsch, Panagiotis Germanakos, and Lynn Huestegge. 2020. Toward a Taxonomy for Adaptive Data Visualization in Analytics Applications. *Frontiers Artif. Intell.* 3 (2020), 9.

[24] Data Protection. [n.d.]. Rules for the Protection of Personal Data Inside and Outside the EU. 2018. *Retrieved from European Comission: https://ec. europa. eu/info/law/law-topic/data-protection_en* ([n. d.]).

[25] Bahador Saket, Alex Endert, and Çağatay Demiralp. 2019. Task-Based Effectiveness of Basic Visualizations. *IEEE Transactions on Visualization and Computer Graphics* 25, 7 (2019), 2505–2512. https://doi.org/10.1109/TVCG.2018.2829750

[26] Ben Steichen, Giuseppe Carenini, and Cristina Conati. 2013. User-adaptive information visualization: using eye gaze data to infer visualization tasks and user cognitive abilities. In *Proceedings of the 2013 international conference on Intelligent user interfaces*. 317–328.

[27] Ben Steichen and Bo Fu. 2019. Towards Adaptive Information Visualization-A Study of Information Visualization Aids and the Role of User Cognitive Style. *Frontiers in Artificial Intelligence* 2 (2019), 22.

[28] Dereck Toker, Cristina Conati, Giuseppe Carenini, and Mona Haraty. 2012. Towards adaptive information visualization: on the influence of user characteristics. In *International conference on user modeling, adaptation, and personalization*. Springer, 274–285.

[29] Dereck Toker, Cristina Conati, Ben Steichen, and Giuseppe Carenini. 2013. Individual user characteristics and information visualization: connecting the dots through eye tracking. In *proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 295–304.

[30] Dereck Toker, Sébastien Lallé, and Cristina Conati. 2017. Pupillometry and head distance to the screen to predict skill acquisition during information visualization tasks. In *Proceedings of the 22nd International Conference on Intelligent User Interfaces*. 221–231.

[31] Usability.gov. 2021. Personas, accessed on Mar. 1, 2021.

[32] Maria C Velez, Deborah Silver, and Marilyn Tremaine. 2005. Understanding visualization through spatial ability differences. In *VIS 05. IEEE Visualization, 2005.* IEEE, 511–518.

[33] Peter Walla. 2018. Affective processing guides behavior and emotions communicate feelings: Towards a guideline for the NeuroIS community. In *Information systems and neuroscience*. Springer, 141–150.

[34] Herman A Witkin, Carol Ann Moore, Philip K Oltman, Donald R Goodenough, Florence Friedman, David R Owen, and Evelyn Raskin. 1977. Role of the field-dependent and field-independent cognitive styles in academic evolution: a longitudinal study. *Journal of educational psychology* 69, 3 (1977), 197.

[35] Caroline Ziemkiewicz and Robert Kosara. 2009. Preconceptions and individual differences in understanding visual metaphors. In *Computer Graphics Forum*, Vol. 28. Wiley Online Library, 911–918.