Emerging Models of Care Using IT in Long-Term/Post-Acute Care: A Comparative Analysis of Human and AI–Driven Qualitative Insights

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ABSTRACT

PURPOSE: As the global population ages, long-term/post-acute care (LTPAC) systems face challenges in ensuring quality care for older adults with complex medical needs. Using health information technology (IT) is a promising strategy to address these challenges. However, evidence gaps remain regarding barriers and facilitators to technology integration in LTPAC. Thus, the current study explored barriers and facilitators to technology adoption in emerging models of care for older adults through the International Summit on Innovation and Technology for the Care of Older People (IS-ITCOP).

METHOD: The IS-ITCOP Summit, held in June 2024, brought together 47 interdisciplinary experts from eight countries. Qualitative data were collected via facilitated discussion groups and analyzed using two approaches: human-coded thematic analysis and ChatGPT 4.0-driven analysis.

RESULTS: Shared themes included technology barriers, ethical considerations, workforce challenges, and patient-centered care. Human analysis emphasized abstract themes, whereas ChatGPT provided granular insights on emerging technologies.

CONCLUSION: Combining human and artificial intelligence–driven analyses enriched understanding, highlighting opportunities and challenges for integrating IT into LTPAC systems. [*Journal of Gerontological Nursing, 51*(4), 6-11.]

By 2050, the proportion of the world's population that is aged ≥60 years will almost double from 12% to 22%, representing approximately 2 billion older people worldwide (World Health Organization [WHO], 2024). As the world's population ages, many challenges exist for providing safe, higher quality care for older adults (Anderson & Prohaska, 2014). Older adults in long-term/post-acute care (LTPAC) have a high degree of medical complexity, often including increasing functional decline and cognitive impairment. In addition, older adults in LTPAC are frequently cared for in low resource settings (Ko et al., 2018). In the current article, we define *LTPAC* as home care and hospice, assisted living and rehabilitation facilities, and nursing homes. One international strategy for improving quality of care in LTPAC is the efficient and competent use of health information technology (IT) (Alexander et al., 2020). Revolutionary innovations and the emergence of IT in health care is accelerating at an unprecedented rate. For example, artificial intelligence (AI) for detecting, diagnosing, and treating disease; virtual reality (VR) for treating pain and mental health conditions; and sensors for monitoring mobility (Ellerbeck, 2023). Unfortunately, there are still many gaps in our evidence about the barriers and facilitators for emerging technologies used to support care of older people in LTPAC.

IS-ITCOP SUMMIT PROCEEDINGS

The current article describes outcomes of the International Summit on Innovation and Technology for the Care of Older People (IS-ITCOP) designed to identify barriers and facilitators to technology adoption in LTPAC. In early 2024, a summit planning committee was formed and began having monthly meetings via an audioconferencing platform to develop the summit objectives and agenda.

The committee, which had national and international experts, was chaired by Gregory Alexander and co-chaired by Anne Livingstone. The Scientific Program Committee (SPC) assembled for this conference included six experts who had significant expertise in policy, engineering, research, informatics, medicine, nursing, and quality in LTPAC systems for older people. During organizing meetings, we distributed tasks, such as solidifying agendas, identifying speakers and participants, and preparing conference materials among the team. On June 6-7, 2024, attendees met in New York City at Columbia University School of Nursing for IS-ITCOP.

The current report provides an overview of two analytic methods for qualitative synthesis, including analysis by a human and a ChatGPT 4.0 large language model (LLM) focusing on IS-ITCOP discussions about emerging models of care (EMC) incorporating technology in the care of older adults. Results of both analytic methods are compared. In addition, analysis of discussions helped us meet our primary objective for IS-ITCOP: to identify barriers and facilitators of technology adoption in LTPAC EMC. The Institutional Review Board determined that this project was not human subjects research.

METHOD

Participants

IS-ITCOP created an opportunity for 47 internationally known interdisciplinary experts, including gerontologists, physicians, nurses, informatics experts, administrators, researchers, quality improvement experts, and economists, to come together to develop shared knowledge, identify and overcome barriers, and define methodologies to identify barriers and facilitators for IT use among older adults in LTPAC. Participants who attended represented the United States, Australia, Canada, Norway, the Netherlands, Taiwan, India, and the United Kingdom. Although there are profession-based conferences in nursing, medicine, informatics, and other disciplines, there are limited opportunities for focused interdisciplinary dialogue on care delivery systems using technology in the care of older people in LTPAC. Bringing together these experts in a conference format allowed the team to generate ideas, brainstorm, and identify barriers and facilitators for IT use in EMC for older adults.

Data Collection

Discussions about EMC using technology in the care of older adults were conducted on the morning of June 6, 2024. Prior to starting EMC discussions, the Chair (G.L.A.) gave an overview of the IS-ITCOP goals, agenda, and introductions of guests. Following the opening, a keynote was given by an expert (R.K.) on EMC using technology in the care of older adults in LTPAC settings. After the keynote, participants transitioned into discussion groups with four to six people per group. In each group, an experienced facilitator led discussions using a semi-structured guide recommended by the SPC developed using a rigorous systematic framework (Kallio et al., 2016). **Table B** (available in the online version of this article) provides a list of semi-structured questions that were used by facilitators to guide participants' discussions. To enhance rigor and achieve expanded descriptions of qualitative discussions, facilitators were encouraged to probe into areas that needed more clarification as interviews were conducted. Each discussion group had a timekeeper who kept discussions to 60 minutes and a recorder who documented discussions digitally.

In addition, recorders in collaboration with facilitators captured excerpts during conversations, including key words of important discussion topics in a computer program called Slido (https://www.slido.com/). Using Slido,

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the submitted words are displayed collectively as a word cloud, with the size of each word indicating its popularity or frequency of submission across discussion groups. This real-time visualization provided a snapshot of group sentiment, opinions, and ideas generated during discussions. Excerpts and keywords from each discussion group were downloaded after the discussions. Data from all discussion groups were aggregated and organized into a word cloud that was used as a tool by facilitators to report to all IS-ITCOP attendees. At the conclusion of each day, each facilitator of a discussion group reported to all IS-ITCOP attendees addressing contents of the word cloud in a summary of their discussions. Attendees were encouraged to comment to the group on contents of each word cloud. In this way, we established some credibility and confirmability of the discussion group content (Lincoln & Guba, 1985). Throughout the conference, all sessions were recorded and transcribed verbatim. The transcripts were used in the analysis and writing of the results of the summit.

Data Analysis

Verbatim transcripts were used in two separate analysis methods: (1) human analysis with rigorous proven qualitative coding methods; and (2) thematic inquiries using newer AI driven generative LLM (i.e., ChatGPT 4.0) methods. NVivo software was used to complete the qualitative human analysis. In the second analysis, ChatGPT 4.0 was conducted in a duo authenticated enterprise sandbox maintained by Columbia University. Investigators elected to use two separate analyses, including proven gold standard qualitative methods and less proven LLM methods where more research is needed (Bijker et al., 2024). A methods comparison study was used to help determine whether the newer analysis techniques are equivalent to the gold standard method (Hanneman, 2008). All coding methods were conducted by two authors (G.L.A. and S.H. [a postdoctoral fellow who is an advanced practice RN with LTPAC experience]).

Human Analysis. Systematic coding of textual material is a key aspect of qualitative data analysis (Strauss & Corbin, 1990). Human analysis of the IS-ITCOP data included inductive iterative coding processes to identify words or short phrases to capture what was happening among pieces of qualitative data that linked them to broad concepts (e.g., conceptual, relationship, perspective codes) (Bradley et al., 2007). Our systematic process included a codebook with codes, definitions, examples of when to use the codes, keywords, and quoted material obtained from breaking the text down into meaningful data segments (MacQueen et al., 1998). Two coders began by reviewing three discussion group files, then coders met to review and align codes and definitions as a form of member checking for consistency (Guba, 1981). Through the process of tracking codes and definitional changes, investigators maintained an audit trail that provided evidence of thematic development and saturation (Kerr et al., 2010). Additional discussion group files were added until all 10 discussion groups were completely coded and definitions were agreed upon.

ChatGPT 4.0 Analysis. Thematic inquiries using AI-driven ChatGPT 4.0 are becoming an important methodological consideration when generating descriptive and thematically relevant codes and identifying emerging patterns in complex qualitative datasets (Turobov et al., 2024). ChatGPT has been trained extensively on text data to facilitate understanding language structure, semantics, and context (Giray, 2023). However, there have been limitations in using ChatGPT for qualitative research, including currency of data the LLM is trained on, amplifying bias, and the potential for confabulated output (Kantor, 2023). Considering these limitations, analyzing qualitative data using human analysis in conjunction with ChatGPT is still an important methodological approach and one we incorporated in this analysis.

We incorporated some elements of a research protocol by Goyanes et al. (2024) that used ChatGPT for thematic analysis of interview data. First, data were prepared by organizing each of the transcripts for the EMC discussion groups into separate files with consistent headings and labels (i.e., EMC_RecorderX_am1, EMC_RecorderX_am2). In the analysis, this approach facilitated ChatGPT's ability to identify specific texts, including excerpts and quoted material from discussion groups that related to distinct themes identified in the data output. Second, data were uploaded into ChatGPT. The team tested ChatGPT's ability to process all 10 discussion groups at once versus gradually loading discussion groups one at a time. At the same time, the team engineered a series of prompts to define the analysis process for ChatGPT. Prompt engineering involves creating prompt instructions (i.e., tasks that guide the model's behavior), providing context (i.e., external information) to enhance background knowledge to the model, creating input data (i.e., question for the model to process), and specifying an output indicator (i.e., type and format of output) (Giray, 2023). These processes helped achieve an acceptable level of saturation using the LLM, defined as discussions by all recorders being represented in the output. We maximized results by incrementally adding discussion files (i.e., up to five at a time), writing relevant prompts, refining prompts, comparing pros and cons of prompts, and making decisions about which prompts provided optimal instructions (Bijker et al., 2024). **Table C** (available in the online version of this article) illustrates the five prompts used in the thematic analysis.

RESULTS

Results include findings from our systematic testing using human analysis and ChatGPT 4.0 techniques for qualitative analysis. In addition, a

comparison of human and ChatGPT 4.0 analyses of IS-ITCOP includes common insights and differences in barriers and facilitators recognized by experts for using IT in EMC for older adults in LTPAC.

Testing ChatGPT 4.0 Analytical Approach

Systematically testing the ChatGPT analytical approach was an important step to determine how much discussion data to upload (e.g., incremental file upload vs. all at once). Testing proved that smaller subsets of five discussion groups worked better than all 10 discussion groups at once. Coordinating the amount of data to upload into ChatGPT provided a means to examine the output to ensure that ChatGPT had extracted relevant information for each of the recorders who documented conversations in the discussion groups.

Saturation and Information Extraction Techniques

The total word count for each of the individual discussion group files ranged from 8,567 to 12,498 words. During some tests, when more than five files were uploaded, excerpts from some of the recorders were not included in the output. In our assessment of this approach, extracting information from each of the discussion sessions was an important indicator of saturation in our ChatGPT output. The mean word counts for the final two sets of five files uploaded into the LLM were 9,921 and 10,997, respectively. The incremental loading of discussion group texts was preferred over the all-at-once approach because the output aligned with our expectations given the prompts (**Table C**) engineered into our analysis. This approach is consistent with other research using ChatGPT for thematic analysis (Goyanes et al., 2024).

Comparison of Human and ChatGPT Analyses

Table D and **Table E** (available in the online version of this article) provide the results of human analysis and ChatGPT analysis, respectively. Shared core themes emerging from these independent analyses include *Technology Barriers*, *Ethical Considerations*, *Workforce and Training*, and *Patient-Centered Care*.

Common Insights on Challenges and Benefits of Technology Integration. Both analyses identified barriers to technology adoption, including infrastructure challenges, interoperability issues, and usability concerns. Ethical considerations materializing out of the discussions were about privacy, security, and trust, reflecting a common emphasis among the discussion groups on technology's ethical and human impact. Both analyses discussed challenges in the workforce, including competency, training, and managing technology's role in care delivery. Another theme surfacing in both analyses focused on patient-centered care and the importance of personalizing and customizing care delivery through technology. Both analyses weigh the advantages (e.g., efficiency, independence, improved collaboration) against the challenges (e.g., trust, scalability, costs) of integrating technology into EMC. Finally, both analyses emphasized technology's role in collaboration among care teams and families and to achieve improved outcomes in LTPAC.

Differences Between Human and ChatGPT Analysis. In addition to the commonalities discussed above there were also some differences noted between the analyses, specifically in the granularity and detail, ethical nuances, technology focus, socioeconomic disparities, and emphasis on innovation and scalability. Regarding granularity and detail of the human analysis (**Table D**), the content appeared to provide a broader perspective with more emphasis on high-level themes such as "Determinants of Emerging Models," "Barriers of Technology," and "Benefits of Technology." Human analysis also incorporated some abstract concepts, such as dignity, humanity, and power dynamics. In contrast, the ChatGPT analysis (**Table E**) delved into specific subthemes and technologies (e.g., wearables, robotics, VR). Furthermore, the ChatGPT analysis provided detailed examples of technologies and their applications (e.g., smart lifts, cognitive orthotics).

There are ethical nuances noted between the two analyses. For example, the human analysis content in **Table D** emphasizes person-centered care and humanity, focusing on themes such as compassionate ageism and autonomy, whereas the content of the ChatGPT analysis (**Table E**) explored ethical considerations in greater detail regarding data ownership, algorithmic bias, and transparency. Considering the technology focus in the discussions, the human analysis appeared to focus on technology benefits in broad categories, such as "support transitions" and "home-based HIT innovation." Alternatively, the ChatGPT analysis focused more on emerging technologies, such as robotics, AI, VR, and predictive analytics, which reflects a forward-looking perspective. There are also differences in how socioeconomic disparities are perceived between the two analyses. For instance, the human analysis discussed barriers, such as "social determinants of health" and organizational limitations broadly, whereas the content of the ChatGPT analysis highlighted disparities more explicitly, including "two-tiered systems of care" and the "digital divide," offering socioeconomic insights into EMC using technology for older people. The content of the ChatGPT analysis included themes on scalability (e.g., regulatory hurdles, financial models) and highlighted cutting-edge innovations, such as VR and exoskeletons, which are less prominent in the human analysis content.

Shared and Unique Themes From Both Analyses. **Table F** (available in the online version of this article) provides examples of exemplar quotes for each shared core theme from the qualitative analyses.

DISCUSSION

The two analyses conducted in the current study, human and ChatGPT, were complementary to each other. Results of the analyses highlight shared themes among participants in the IS-ITCOP discussions on EMC including technology barriers, ethical considerations, workforce and training, and patient-centered care. However, there were also some differences noted between analyses. For example, the human analysis resulted in broader, higher-level themes that were represented by concepts that were more abstract in nature. In contrast, ChatGPT analysis resulted in subthemes addressing specific applied technologies emerging in the care of older adults. Some of these differences may be attributable to the degree of prompt engineering used in ChatGPT analysis to derive themes from discussions (Goyanes et al., 2024).

Although the analyses were complementary, a comparison of these two analytic approaches illustrates strengths and weaknesses. In the human analysis, there appears to be a deeper understanding of the human-centric themes (e.g., autonomy, dignity) but there is less granularity about specific technologies discussed by participants. In the ChatGPT analysis, the content provides a detailed exploration of emerging technologies (e.g., robotics, wearables), but there is potential for biases and lack of nuanced contextual understanding of these innovations in the care of older adults. As a result, combining both qualitative approaches into an analysis have enriched the thematic insights in different ways, allowing for a deeper understanding of the discussions overall. However, more exemplars using LLM as a substitute for gold standard qualitative analysis are needed before we can be certain of the efficacy of its use in this way (Khraisha et al., 2024; Konet et al., 2024).

Results of the current qualitative analysis unveil important implications for leaders of LTPAC settings considering technology in EMC for older adults. There are important technological examples (e.g., AI) drawn out of discussions that experts believe are new opportunities to address the challenges of caring for older adults. However, experts expressed that there are significant hurdles that leaders of LTPAC organizations must clear before some emerging technologies will be safe or ready to use in these settings (e.g., interoperability, digital divide between care settings). Policy and regulatory actions, including the development of standards for improved interoperability, transparency, and safeguards to ensure equitable access to mitigate ethical risks, are paramount to support EMC using technology in the care of older people in LTPAC.

CLINICAL IMPLICATIONS

Findings from the IS-ITCOP have significant clinical implications for nurses working in LTPAC settings. As frontline caregivers, nurses play a critical role in adopting and implementing emerging technologies to enhance patient outcomes and streamline care processes. The shared themes of technology barriers, workforce challenges, and ethical considerations highlight the need for targeted training programs to build competency in using advanced technologies, such as AI, VR, and sensors. Nurses must also advocate for patient-centered approaches, ensuring that technology adoption aligns with the unique needs and preferences of older adults in LTPAC. Addressing barriers, such as interoperability and usability issues, will empower nurses to use technology for improving efficiency and collaboration in care delivery. Furthermore, the study underscores the importance of involving nurses in discussions about ethical challenges, such as data privacy and equity, to ensure technology integration respects patients' dignity and autonomy.

CONCLUSION

Two approaches (human analysis and ChatGPT) were used to analyze qualitative data about EMC using technology in the care of older people in LTPAC. Human analysis provided a holistic, qualitative summary emphasizing conceptual frameworks, humanity, and policy-level determinants. In contrast, ChatGPT analysis adopted a detailed, technology-centric lens, offering practical and future-oriented insights. Together, these approaches complement each other, providing a comprehensive understanding of technology's impact on EMC for older people.

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Table A

International Summit on Innovation and Technology for the Care of Older People (IS-ITCOP) Participants (in alphabetical order)

Julia Adler-Milstein, PhD, University of California
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Ulf B. Bronas, PhD, Columbia University
Sam Brooks, JD, Consumer Voice
Jennene Buckley, BB, Enkindle
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Michelle Dougherty, MA, RTI
Marjolein den Ouden, PhD, Saxion University of Applied Sciences
Colleen Galambos, PhD, MSW, University of Milwaukee
Rose Lai, PhD, RN, Commerce Development Research Institute
Robert Latz, DPT, Trinity Rehabilitation Services
Isaac Longobardi, BA, LeadingAge
Lisa Morris, MSc-BMI, Consana
Lorren Pettit, MS, MBA, Gerotrend Research
Jingjing Shang, PhD, RN, Columbia University School of Nursing
Kavita Sivaramakrishnan, PhD, Columbia University
Victoria L. Tiase, PhD, RN, University of Utah
Maxim Topaz, PhD, RN, Columbia University School of Nursing

Table B

Roundtable Discussion Questions Day 1, AM Session

Topic: Emerging Models of Care and Technology

AM Roundtable 1

- **Evaluate the effectiveness and efficiency of current technological solutions in addressing the unique needs of older adults in long-term care.**
- **Examine the role of artificial intelligence, robotics, telemedicine, and other innovative technologies in enhancing the quality of care for older adults in long-term care settings.**

1. In what ways do emerging technologies offer potential improvements in long-term care for older adults, and what are the main obstacles to their widespread adoption in these settings?
2. How might the integration of emerging technologies into existing long-term care models impact the quality of life and independence of older adults?
3. What are some examples of how artificial intelligence is currently being used to personalize care plans and improve health outcomes for older adults in long-term care settings?
4. What role does robotics play in supporting the activities of daily living for older adults in long-term care? How can they contribute to efficiency and cost-effectiveness in these settings?
5. How can telemedicine technologies facilitate better access to healthcare services for older adults in long-term care, particularly those in rural or underserved areas?

AM Roundtable 2

- **Discuss the ethical considerations and implications of using technology in the care of older adults, including issues related to disparities in patient outcomes.**

- **Explore the potential benefits and challenges of integrating emerging technologies into existing long-term care models for older adults.**

6. How do current technological solutions in long-term care address the specific needs and challenges faced by older adults, such as mobility issues, cognitive decline, and social isolation?
7. What are the potential ethical concerns surrounding the use of technology in the care of older adults, and how can these be addressed to ensure patient safety and autonomy?
8. How might disparities in access to and proficiency with technology impact the quality of care received by older adults in long-term care settings, and what strategies can be implemented to mitigate these disparities?
9. What are some potential unintended consequences of relying heavily on technology in the care of older adults, and how can these be minimized or avoided?
10. In what ways can policymakers, healthcare providers, and technology developers collaborate to ensure that the benefits of technological innovation in long-term care are equitably distributed among older adults of diverse socioeconomic backgrounds?

Table C. Prompts used for ChatGPT 4.0 Analysis

Prompt 1	We have attached 5 interviews. Please do not take any action, just indicate whether or not you have incorporated the interviews.
Prompt 2	Identify as exhaustively as possible the most recurring themes considering the content of the five discussions we have uploaded.
Prompt 3	Search for and list key phrases or terms related to the specific topics listed in the previous prompt.
Prompt 4	Make a table illustrating the themes and subthemes identified in the two prior prompts. Respond with identified topics, associated keywords, and relevant text excerpts.
Prompt 5	Provide a list of direct quotes from the attached interviews that represent each of the themes identified in the previous prompt.

Table D. Human Analysis of IS-ITCOP Emerging Models of Care Discussions

Theme	Secondary Themes	Key Words
Barriers of Technology	Technology Issue	Generalizability, Telehealth, Technology Fail
	Person Centric Barriers	Adoption/Usability, Alarm/Alert Fatigue
	Organizational Barriers	Workforce Competency, Technology Infrastructure, Attention to Resources, Interoperability
	Community Level Barriers	Social Determinants of Health, Costs, Policy, Culture
Benefits of Technology	Patient/Family Impact	Sustaining/Improving Independence, Social Engagement, Dementia Care, Telehealth Impact, Home Based HIT Innovation, Support Transitions, Dignity/Humanity, Assisting Mobility
	Workforce Support	Efficiency/Time, Improved Collaborations, Alleviate Burden, Training/Education, Staffing, Improved Assessment, Monitoring, Prevention, Prediction, Enhanced Communication / Decision Making, Information Capture, Tracking Resources
Determinants of Emerging Models	Policy Inter-collaboration and Shared Understanding Adoption/Usability Training/Education Patient-Centered Care Affordability Collaboration between Humans and Technology Interoperability Mutual Respect Supply and Demand	Need for Regulation and Standards, Finance, Reporting of Outcomes Based on Care Models, Compliance, Improvement in Disparities Providers and Patient's Rights, Frontline Staff Involvement, Replacing Humans with Computers, Customization
Ethical Considerations	Technology Integrity	Trust, Safety, Security, Privacy, User Centered Design, Unexpected outcomes, Validation/Accuracy in Clinical Use, Dependency risk/over-reliance, Telehealth, Bias in Data
Power Dynamics and Social Structure	Dignity and humanity	Person-Centered Care, Autonomy, Literacy, Compassionate Ageism, Inclusivity and Vulnerable Populations, Inhumanity

Table E. ChatGPT Analysis of IS-IT COP Emerging Models of Care Discussions

Theme	Secondary Themes	Key Words
Challenges in Technology Adoption	Technology Infrastructure	Wifi (i.e., Internet) Digital Infrastructure, Facilities, Rural Areas
	Staff Training / Acceptance	Workforce Competency, Engagement, Training for AI Use
	Trust in Technology	Trust in AI systems, Recommendations related to patient goals
Emerging Technology in Long Term Care	Efficiency and Quality of Care	Wearables, Telehealth, Robotics
	Data Collection and Analysis	Remote Monitoring, Vital Signs, Behavioral Changes, Human Interaction, Automation
	Predictive Analytics	Risk Prediction Trajectories, Proactive Care, Early Intervention
Customization and Personalization	Patient Centered Technology Automation vs. Human Interaction	
Data Ownership, Privacy and Ethics	Data Privacy and Security Ethical Concerns Transparency and Consent Autonomy	Breach of Trust, Data Handling and Sharing
Workforce and Staff Empowerment	Relieving Administrative Burden Empowerment of Caregivers Caregiver Burden Two tiered systems of care	 Wealthier facilities versus underfunded facilities
Patient Autonomy and Independence	Aging in Place Self-Management Tools	
Interdisciplinary Collaboration and Care Models	Integration Across Care Teams Care Models of the Future	
Barriers to Scaling Innovations	Cost and Financial Models Regulatory Hurdles	
Role of Family and Caregivers	Family Engagement Support for Caregivers	
Technology Solutions in Long Term Care	Mobility Support Cognitive Decline Social Isolation	Bed sensors, smart lifts, fall detection, exoskeletons Cognitive orthotics, AI, mobile games, remote monitoring, early detection Robotics, Video Platforms
Ethical Concerns	Algorithmic bias	
Disparities in Access and Technological Proficiency	Digital Divide Technological Proficiency	Rural and Underfunded facilities Technology Used to Full Potential
Impact of technology on Care Quality	Efficiency vs. Human Interaction Preventative and Personalized Care	Automation and Frequency of Human Checks Early intervention

Adoption of Emerging Technologies	Robotics and AI Virtual Reality Wearables
Integration and Interoperability	Efficiency in Care Coordination
Human Centered Design	User Involvement Age Appropriate Technology

Table F. Shared Themes, Subthemes, and Quotes Derived from Human and ChatGPT Analysis

Shared Themes	Analysis Type	Subtheme	Direct Exemplar Quotes Representing Themes/Subthemes
Technology Barriers	Human	Adoption and Usability	*“And we have so many units. I mean, in long-term care, you have people that are maybe all a very high risk for falls. And so what do you do with that? It's part of the data deluge and information deluge without it being actionable or without it being really knowledge.”*
	ChatGPT	Technology Infrastructure	*“And yes, I think that although it's not asking for barriers, but it's the infrastructure piece again, because if you're in older buildings, you can't get the signal to the robot, and we can't map the older buildings."* *“And so, there's an inherent disparity just in the infrastructure required to support this digital revolution and all the technology that comes with it.”*
Ethical Considerations	Human	Trust, Safety, Security, Privacy	*“I think people that tend to focus so much on issues of privacy that I think that it's losing what you're saying, basically, that there's so much data available. It's just not a question of who is collecting data about me and how is it going to get out in the open or whatever. …but they're collecting so much data in quantity.”*
	ChatGPT	Trust in Technology	*"…we need to be able to trust the data that's being collected in order for the analyses to be made and the outcomes to be valid. So, I think that's a very, very important point, actually, because we've got all kinds of inequalities."*
Workforce and Training	Human	Workforce Support	*“And the other thing that [NAME] could talk a lot more about and will later today is really the competency of the workforce to really engage to have a technology enabled engagement because there's a lot of variation in the technological competencies of individuals in that, that long-term care workforce.”*
	ChatGPT	Staff Training and Acceptance	*" And I think that the challenge is we have to train everybody at a higher competency level with IT that we don't have the time to train them at that level, or we don't have the resources or wherewithal to choose to do that, so."*
Person-Centered Care	Human	Dignity and Humanity	*“Yeah, it's sort of like the people with their kids. Hand them an iPad now. Before you interact with your kid, now hand them an iPad and entertain them for a couple hours. Yeah, I guess it could be an important thing to really think about how that's addressed, and that's more of that care planning process. But ethically, I mean, it's-ethically, you're isolating them more sometimes if it's not an interactive, engaging type of access to technology.”*
	ChatGPT	Age-Appropriate Technology	*“I think in everything you read, the limitation in every single paper it feels like is that we recruited a convenient sample of individuals that were interested in using technology. So how are we getting at designing these solutions for folks that don't use it that might want to?”*