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Codesign and AI: AI-assisted clustering of perception patterns of seniors on ageing and technology in Singapore

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ABSTRACT: AI-assisted methodologies captured lived experiences and enhanced innovation practices, supporting practitioners, policymakers, and researchers in designing ageing technology. This study examined AI-assisted methods, leveraging open conversations with 30 seniors to address the complexities of ageing and technology in Singapore. Using prompt engineering, we analysed coded data with role-based, context-providing, and information-seeking prompts, generating Python code for clustering analysis. The focus was on seniors' perceptions of technology and health concerns, revealing 25 indicators across six health dimensions. Of these, 12 social-emotional determinants influenced perceptions through emotional support and social interaction on technology adoption. Our analysis produced a four-cluster typology, providing a systematic framework to categorise perception patterns and address seniors' diverse needs.

KEYWORDS: ageing, technology, collaborative design, artificial intelligence, kernel k-means clustering

1. Introduction

Societies worldwide are witnessing a rapidly ageing population. According to the World Health Organisation (WHO) in 2020, the number of individuals aged 60 and above surpassed the number of children under the age of five, while by 2050, the global population aged over sixty is projected to nearly double, increasing from 12% to 22% (WHO, 2024). This highlights that population ageing has become a preeminent global phenomenon that cannot be overlooked, placing significant demands on social and healthcare systems (Breyer et al., 2010). The European Commission (EC) forecasts that these demographic changes will raise public healthcare expenditure in EU Member States by an average of 1.1 percentage points of GDP, from 6.8% to 7.9%, between 2016 and 2060 (European Commission, 2018). Consequently, there has been a growing emphasis on research and development in the senior health sector for cost-effective, innovative solutions to enhance elderly care while ensuring long-term sustainability (Cristea et al., 2020).

1.1. Aim and significance

Referencing the public healthcare expenditure trends in the EU to ageing-related challenges in Singapore, our study aims to understand seniors' perceptions and adoption of technologies by using AI-assisted clustering techniques as a data analysis method to inform future technology innovations in ageing. We developed a codesign methodology that leverages AI's unique capabilities to categorise data collected about perceptions, opinions, and feelings for research. Prompt engineering and the clustering method were explored to categorise seniors' perceptions of technology. This approach enables researchers to derive actionable insights from complex, qualitative datasets. Two research questions (RQs) were answered based on coded data of self-reported observations when interacting with seniors:

- **RQ1**: How can AI assist in clustering perception patterns of technology in an ageing study?
- **RQ2**: How can we develop a typology to describe seniors' perception patterns by clusters?

With our results, this study offers a novel framework for design researchers, practitioners, and policymakers to integrate codesign and AI. we adopt a codesign methodology integrated with AI in categorising, analysing, and interpreting seniors' self-reported perceptions, opinions, and feelings. Through AI-assisted experiments, prompt engineering and clustering techniques were applied to extract meaningful insights from complex qualitative datasets. Our paper is distinct from previous work two ways. Firstly, we adopted co-design approach combined with Kernel K-means clustering method to identify seniors' technology perception levels. With a focus on social-emotional factors, design researchers are enabled to address seniors' actual needs. Secondly, we co-developed the SCOPE sensemaking framework for a guidance in using GPT's responses for research.

2. Literature review

Ageing technology encompasses digital innovations designed to meet the needs and preferences of older adults, enhancing their quality of life. As populations age rapidly, ensuring adequate care over long distances is becoming increasingly urgent (Toh, 2017). Addressing the socioeconomic challenges associated with ageing requires a greater emphasis on healthcare and technology adoption to improve well-being. Key factors influencing the use of technology as an enabler include barriers—such as lack of instructions, limited knowledge and confidence, health conditions, and cost (Eleftheria et al., 2017)—and enablers, which focus on integrating personal care, social support, clinical services, and daily living assistance, including transport (Kaplan et al., 2022). With the rapid advancement of the Internet of Things (IoT), big data, and artificial intelligence (AI), new opportunities are emerging to address the diverse needs of older adults (Lee et al., 2019; Lee et al., 2022; Lee, 2022). Life events, age-related decline, shifting personal goals, and social influences shape technology adoption at different life stages (Peek et al., 2019). AI and digital technologies have shown promise in supporting an ageing population (Czaja & Lee, 2012). Studies highlight AI's application in senior healthcare, including geriatrics (Koç, 2023), fall prevention and emergency intervention (Mohan et al., 2023), and cataract surgeries (Teodoru et al., 2023). Research also underscores the positive impact of digital technologies on older adults' quality of life (Ali et al., 2022). Beyond healthcare, AI-driven thematic analysis has been applied to understand seniors' experiences with technology, such as tablets (Vaportzis et al., 2017).

While these innovations offer significant benefits, their adoption depends on seniors' willingness to engage with technology. Studies have explored key factors influencing technology acceptance (Phang et al., 2006; Tsertsidis et al., 2019), identifying barriers such as low confidence, perceived complexity, and limited peer support (Charness & Boot, 2009; Green & Bavelier, 2008; Boot et al., 2011). Addressing these challenges is essential for ensuring that ageing technologies are designed for the target audience before assessing whether they are available, widely adopted, and effectively used.

More studies need to be conducted using AI-driven methods to explore the nuanced perceptions of seniors. Traditional k-means clustering assumes linear separability, which can limit its effectiveness on complex datasets. A kernel function maps data points into a higher-dimensional feature space where linear separability is more achievable (Cai et al., 2024). Dimensionality reduction techniques, such as t-distributed Stochastic Neighbour Embedding (t-SNE), simplify the dataset while preserving its structure and enhancing clustering performance by reducing noise and computational complexity (Van der Maaten and Hinton, 2008). This transformation allows the Kernel K-means to identify non-linearly separable clusters in the original space.

3. Methods

Clustering can effectively analyse diverse populations. Scholars adopt AI and clustering methods to analyse the social-emotional factors behind these perceptions (Xu and Tian, 2015; Tao et al., 2023). Our methodology involves a comprehensive study of 30 participants who consolidated opinions/feedback on seniors' responses to technology through open conversations (Blessing and Chakrabarti, 2002; 2009). Compared with conventional semi-structured/structured surveys and interviews, our data collection uses open conversations so that researchers can capture the nuances and better support the development of a typology for clustering seniors' perception patterns (Figure 1).

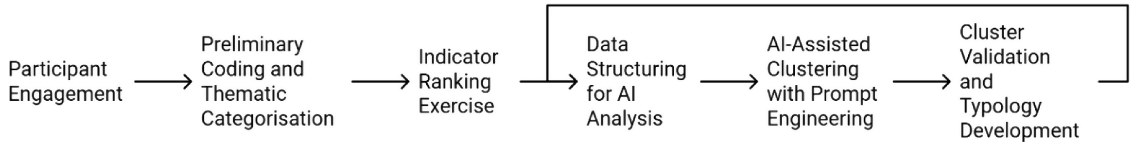

Figure 1. A structured codesign study with open conversations and AI prompting

This systematic procedure draws on Yap et al. (2022) and Siew et al. (2022) to design and guide our thematic analysis and categorisation of technology usage among seniors. Coding and analyses using Kernel K-means clustering with dimensionality reduction technique were performed using Python, which resulted a four-cluster typology of seniors' perception patterns. These methods handled non-linear relationships within the data, allowing for a more nuanced analysis of perception patterns.

3.1. Data collection

Each engagement session took around 60 to 90 minutes, allowing participants to share their perspectives on ageing and technology. The researcher audio-recorded and thoroughly reviewed these sessions to ensure better accuracy afterwards. In adherence to strict confidentiality protocols, personal information, including participants' lived experiences and life stories, was protected through a coding process. Using a template, the researcher captured the thematic responses on the spot. From this, we categorised seniors' pain points and struggles later into themes as participants articulated their actual needs and concerns. Ten indicators were used, describing the success factors of technology based on the uses and perceptions among seniors. The indicators provided a structured basis for guiding our analysis. Participants ranked these ten indicators from 1 to 10 and explained their chosen order (Table 1).

Table 1. Capturing perception patterns by success factors of technology with ten indicators

1	Aesthetics	6	Perceived independence
2	Cost	7	Perceived support
3	Durability	8	Social inclusion
4	Privacy	9	Usability
5	Safety	10	User-interface

3.2. Data analysis using AI

After engaging seniors to learn about their views of ageing and technology, we applied role-based, context-providing, and information-seeking prompts to perform qualitative pattern recognition and clustering of coded data (Yao et al., 2023). Three types of prompting were used in our analysis:

a) **Role-based prompts** – leveraging AI as a domain expert to validate clustering criteria.
b) **Context-providing prompts** – aligning AI-generated responses with the qualitative data.
c) **Information-seeking prompts** – refining clustering accuracy by validating responses against the researcher's recorded data.

A structured procedure was co-developed, referencing relevant literature (Chatterjee and Dethlefs, 2023; Sarker, 2022). We outlined a SCOPE framework for sensemaking using AI prompting, which can allow researchers to explore the use of AI and extract nuances in qualitative data. It also improves reproducibility for GPT's responses during experiments with coded data (Table 2).

Table 2. Applying SCOPE for AI prompting in design research

Action	Goal	Example Prompt
Seek	Defining the roles that AI plays.	"Act as a data scientist specialising in qualitative analysis. How would you categorise these responses?"
Correct	Refining AI's responses	"Align thematic indicators and adjust based on the variables."
Organise	Ensuring structure in AI's responses	"Group these responses into four categories based on technology perception patterns."
Provide	Requesting specific data outputs from AI	"Generate a Python script using Kernel K-means for clustering the following dataset."
Explain	Extracting AI's insights	"Summarise the differences in perception across clusters."

3.3. Ethics

The Singapore University of Technology and Design (SUTD) Institutional Review Board (IRB), SUTD-IRB reference code S-22-509 approved this codesign study. Seniors' engagements were conducted from 8 March 2023 to 9 May 2023 to understand the role of empathy in design. No raw or transcribed data was uploaded to ChatGPT. Data will be discarded six months after the work is published.

4. Findings

Through open conversations, most participants openly shared their thoughts, feelings, and opinions. Our findings showed that at least one-third of the respondents stated 25 indicators (Table 3):

Table 3. Key indicators based on open conversations with 30 seniors

Indicators	Count (n)
Increased cost of daily living	25
Lack of medical adherence	21
Medical costs and liabilities	20
Loss of confidence	20
Lack of peer and community support (e.g., no friends nearby)	19
Lack of awareness to find care support/ medical assistance	19
Loss of appetite or improper meals	18
Lack of knowledge to manage difficulties (at different stages)	18
Lack of support from the community	17
Sense of burdening others	17
Difficulty in travelling (e.g., taking public transport)	17
Loss of communication ability	16
Loss of independence	16
Loss of navigation ability/getting lost	15
Lack of access to senior-friendly facilities/spaces	15
Loss of self-identity (perception about self)	15
Loss of ability relating to an emotional experience	14
Loss of hobbies/leisure	14
Loss of ability to process information/facts	14
Fear of asking for support from others	12
Sense of being left behind by/excluded from society	12
Feeling stressed/fatigued/dread/depressed/frustrated/anxiety	11
Lack of readily available resources to handle the condition	11
Reduced social interaction with others	10
Loss of job and income/financial strain and issues	10

4.1. Social-emotional determinants for technology in ageing

In our method of analysis, two features are considered when we feed in the coded data in our prompts: (a) seniors' perception of technology and (b) their needs and concerns based on their lived experience. Coded data was used in Python, and we employed Kernel K-means clustering. This method allows for more flexible cluster shapes by mapping the data into a higher-dimensional space, enhancing the clustering accuracy for our perception patterns. Perception patterns among seniors were derived from 25 indicators identified in the literature, classified under social and emotional themes. Our study identified the top 12 indicators as underlying factors (e.g., struggles and pain points) essential to designing ageing technology (Table 4).

Using prompt engineering, Kernel K-means clustering with t-SNE dimensionality reduction analysed coded data points. It derived clusters to explain the prominent reasons (or determinants) for the perception patterns from the coded data extracted through open conversations with seniors. We then developed a typology to describe these patterns in technology perception. Seniors' responses were grouped into four profiling clusters, mapped by the comfort level based on perceived use of technology (y-axis) and potential need for technology (x-axis) when they communicated the match or mismatch in technology solutions to their specific needs, e.g., engaging in active ageing centre activities (Figure 2).

Table 4. Top 12 indicators mapped to social and emotional determinants

Determinant	Indicators
Social	S1: Loss of confidence
	S2: Lack of peer and community support (e.g., no friends nearby)
	S3: Loss of communication ability
	S4: Loss of self-identity (i.e., perception about self)
	S5: Loss of hobbies/leisure
	S6: Reduced social interaction with others
Emotional	E1: Sense of burdening others
	E2: Loss of ability relating to an emotional experience
	E3: Loss of ability to process information/facts
	E4: Fear of asking for support from others.
	E5: Sense of being left behind by/excluded from society
	E6: Feeling stressed/fatigued/dread/depressed/frustrated/anxiety

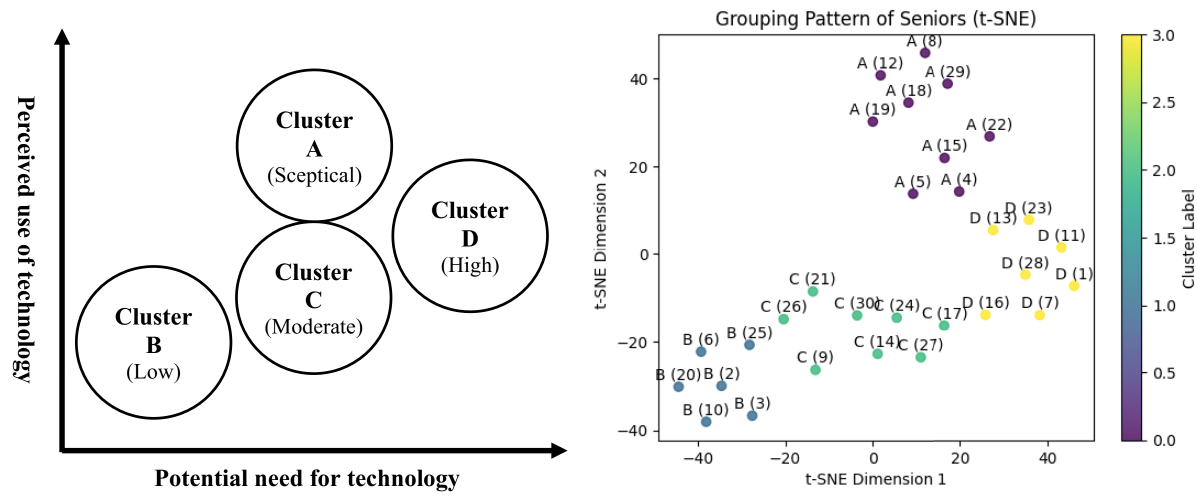

Figure 2. A four-cluster typology of perception patterns towards ageing and technology

Through inductive and deductive analysis, we reasoned that the four clusters were based on their technology perception levels: sceptical, low, moderate, and high:

- **Cluster A** (9 individuals) - Seniors in this cluster represented people with a sceptical perception of technology. They expressed caution in adopting new technologies;
- **Cluster B** (6 individuals) - Seniors in this cluster exhibited a low perception of technology and are reluctant adopters. They showed minimal interest in technology-based solutions;
- **Cluster C** (8 individuals) - Seniors in this cluster displayed a moderate perception of technology. They have a moderate level of technology adoption and utilise digital devices; and
- **Cluster D** (7 individuals) - Seniors in this cluster exhibited a high perception of technology. They are enthusiastic adopters and likely to embrace and actively look for new technologies.

The clustering produced a Silhouette score of 0.4687, reflecting moderate cluster separation and cohesion. The Calinski-Harabasz score was 38.7587, reflecting good cluster compactness and separation, implying distinct technology perception patterns within each senior cluster. Every point on the graph represents a senior participant's needs and concerns according to their perception of ageing and technology.
When deliberating on the four clusters, we uncovered the characteristics and attributes of each cluster. The total count of each cluster in descending order was in the sequence of Cluster D (51), Cluster A (49), Cluster C (43), and Cluster B (31). Cluster D and A (100) count was much higher than Cluster C and B (74) by 26%. Therefore, we cross-referenced our general observations with the social and emotional determinants by the sum of four clusters to explain the patterns (Figure 3).

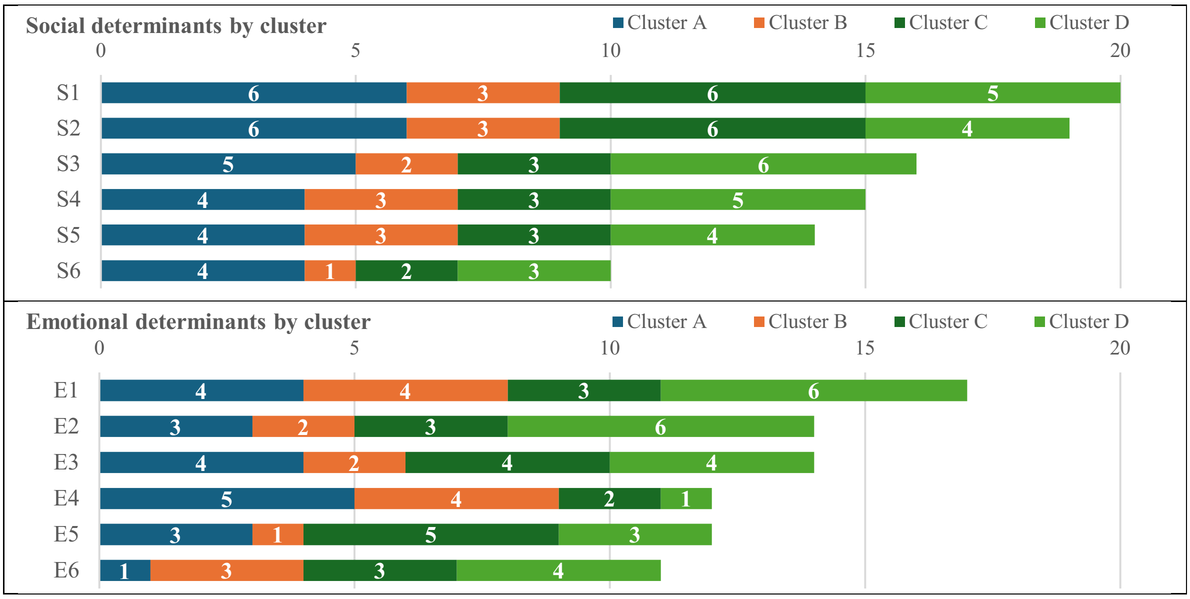

Figure 3. Social and emotional determinants from four clusters

5. Discussion

Context is crucial in ageing technology design, as it shapes how seniors engage with and adopt digital solutions. Thus, this study used AI-driven analysis to examine coded data from the open conversations of 30 participants. Through AI-assisted clustering, four distinct clusters were identified based on ascribed indicators from 30 senior residents across two constituencies. Unlike previous studies, which focus mainly on barriers and enablers of technology use, this analysis incorporated prompt engineering to enhance the visualisation and interpretation of clustered groups in a two-dimensional space. Using Kernel K-Means clustering and t-SNE dimensionality reduction (Paul et al., 2020), further refinement through iterative prompts and clustering adjustments improved cluster interpretability and clearer distinction between adoption levels. The refinement process clarified inter-cluster relationships, supported by descriptive data derived from dimensionality analysis (Vlachos et al., 2002).

As this typology provided a structured framework for categorising qualitative insights, we offer a systematic approach to translate seniors' perception patterns for future studies. Structured qualitative insights and hidden patterns in seniors' technology engagement can support codesign efforts and highlight critical social-emotional factors by understanding how perceived social exclusion and the fear of burdening others can directly influence technology adoption behaviours.

5.1. Practical applications

Pahl and Beitz (1996) emphasise a systematic approach to problem-solving, beginning with a clear definition of design objectives, constraints, and functional requirements in systems improvement. In design practice, this typology can be a foundational framework for pinpointing opportunities and addressing unmet needs in ageing populations. Our findings reinforce the importance of social-emotional considerations in technology design, particularly in understanding how perceived exclusion and emotional concerns shape adoption patterns. Through our typology, we urge design researchers first to understand the need for a structured framework to determine and assess engagement levels. We also provide actionable insights for designers to tailor solutions that align with seniors' needs and concerns. With a human-centred approach, there is a greater chance that ageing technology is practical, inclusive, and emotionally supportive when we can foster greater acceptance of older adults.

5.2. Finetuning and its impact

Our research insights are essential to innovation as they explain seniors' unique needs and concerns before accessibility and usability. We can adopt structured problem-solving and systematic design to strengthen theory development for AI-assisted clustering in research and practice. In doing so, we need to develop ways to empower researchers so that they gain a holistic view of the clustering results using AI. Initially, in our study, the AI-generated Python script applied default parameters to Kernel K-means, which caused an overlap between the "moderate" and "sceptical" clusters. By fine-tuning the number of iterations and initial cluster centroids, along with adjusting prompt structures to distinguish nuances in the data better (e.g., emphasising emotion-related responses), the Silhouette Score improved from 0.40 to 0.47. Moreover, the Calinski-Harabasz Score increased from 35.2 to 38.8, indicating more precise cluster separation. This parameter adjustment reduced ambiguity between moderate and sceptical respondents, validating the role of iterative prompting.

5.3. Enhancement to methodology

Based on our key takeaways from this study, Table 5 outlines our recommendations by describing how to further enhance our methodology's six stages in future research.

Table 5. Recommendations for design research methodology on ageing and technology

Stage	Details	Actions Taken	Recommendations
1	**Participant Engagement**: Conducted open conversations to explore seniors' perceptions of technology.	- 60 to 90-minute per individual session with 30 senior respondents.	- Expand participant diversity to include various socio-economic backgrounds, lived experiences and technology literacy levels.
		- Recorded sessions with strict confidentiality protocols when asking them to share their lived experience on ageing and technology.	- Include visual aids or digital tools during conversations to stimulate better responses and capture more nuanced perceptions.
2	**Preliminary Coding and Thematic Categorisation**: Real-time coding during conversations to capture themes.	- Performed immediate coding to identify themes from responses.	- Establish a coding framework with predefined themes to ensure reliability across researchers.
		- Used pain points identified from prior design sprints with stakeholders.	- Introduce software-assisted coding tools for more efficient and accurate thematic categorisation in real-time.
3	**Indicator Ranking Exercise**: Presented success indicators and gathered rationale behind rankings.	- Captured 30 participants ranking ten success indicators of technology use	- Expand indicators to include cultural or lifestyle factors influencing technology perceptions.
		- Collected explanations to understand reasoning and preferences.	- Use follow-up questions or probes to capture clear explanations and validate participants' reasoning.
4	**Data Structuring and AI Analysis**: Organised data to facilitate analysis.	- Structured coded data into categories aligned with analysis goals.	- Apply data validation techniques to ensure data accuracy aligning with clustering requirements.
		- Prepared dataset for AI-assisted clustering.	- Develop data structuring tools to categorise coded data.
5	**AI-Assisted Clustering with Prompt Engineering**: Applied prompt engineering to guide AI in clustering.	- Experimented role-based, context-providing, and information-seeking prompts for analysis.	- Test additional prompt types, such as clarification prompts, to improve the accuracy of AI's interpretation.
		- Applied Kernel K-means and t-SNE to cluster seniors by technology perception.	- Explore alternative AI models and prompting methods for comparison and choose the one best suited for mixed methods analysis.
6	**Cluster Validation and Typology Development**: Validated and refined clusters to create a typology.	- Refined indicators for better clustering results.	- Introduce a feedback loop with participants to validate the accuracy of clusters and typologies.
		- Developed typology based on four clusters, reflecting technology acceptance and engagement levels.	- Use longitudinal analysis by re-engaging participants over time to observe changes in perceptions.

6. Conclusion

Our design research advances the field of AI prompting by demonstrating how AI can mitigate design fixation (Koronis et al., 2021) and facilitate the development of a typology that expedites concept evaluation and enhances insights translation (Siew et al., 2022; 2023). We designed and utilised the SCOPE framework—Seek, Correct, Organise, Provide, and Explain—to guide AI-assisted clustering in analysing seniors' technology perceptions. This structured, value-based approach enabled researchers to employ ChatGPT to uncover nuanced patterns, effectively characterising seniors' needs and concerns by visualising and describing perception patterns of 30 senior respondents through Kernel K-Means clustering with dimensionality reduction.

Overall, the SCOPE framework allows researchers to explore the use of AI and extract nuances in qualitative data to elucidate and extract valuable insights through thematic analysis with general knowledge and functional expertise. The resulting four-cluster typology can significantly aid innovation leaders in social service agencies, hospital researchers, and university professors in co-creating products and service systems tailored to seniors' nuanced needs. By integrating AI and co-design principles, this typology facilitates stakeholders in systematically addressing social-emotional aspects of design, extending beyond practical needs. Additionally, the typology serves as a guide for identifying opportunities for design innovation, ensuring that technological solutions are sensible and empathetic. The study also illustrates how open conversations can be conducted while safeguarding personal data throughout the research collection and analysis process.

6.1. Limitations

While success factors for technology are used to inform a systematic approach and support thematic categorisation, there are limitations when translating these findings directly into a design journey for innovation. Firstly, there is a potential bias in data collection, coding and cluster analysis due to sample selection and demographics. Secondly, the perception patterns may hold some biases as technology success indicators were drawn from past design sprints with undergraduate students and stakeholders. Thirdly, we added informed insights from past experiences to enrich the application of our thematic framework, but evolving preferences require us to investigate individual motivations and lived experiences that shape technology adoption. Fourthly, the generalisability of the findings requires more research using the same method to derive a more vigorous conclusion and theory development through open conversations and clustering methods using prompt engineering with AI. Lastly, the choice of GPT may also change the methods and results of analysis based on the data captured. The structured prompting approach ensures that the study's methodology and outcomes are human-centred, ethically sound, and aligned to uncover perception patterns within the ageing population. As the quality of AI outputs depends on the contextual detail provided in prompts, we align with the research intent using the SCOPE framework for a better account of the nuances captured from open conversations.

6.2. Future work

Through our findings, we seek to deepen the understanding of seniors' technology perception patterns by exploring design and AI in data collection and analysis robustness and refining the accuracy of clustering outcomes using prompt engineering. Using the SCOPE framework, this study provides structured insights that could benefit researchers studying ageing and technology. The clusters reflect patterns in participant responses, facilitating sense-making in research and future design tasks.

For future work, our proposed typology could evolve and inform researchers, practitioners and program managers, given that each cluster can be finetuned to represent unique group characteristics by demographic. It also enables designers to facilitate focus group discussions tackling specific needs. AI tools like ChatGPT can support these sessions by generating and validating contexts through research or highlighting technology challenges and solutions relevant to every cluster. Future research could develop comprehensive design and AI frameworks to assess seniors' perceptions or apply the identified clusters to inform design decisions. For example, we can create a more thorough and adaptable methodology by expanding participant diversity, refining coding frameworks, incorporating advanced AI techniques, and introducing feedback loops. For research, codesign workshops can be designed to ask teams to identify user personas, develop journey maps, and generate solution prototypes tailored to the unique requirements of each group in specified clusters. One should not unquestioningly accept preliminary observations while applying role-based prompts followed by context-providing and information-seeking prompts. Other proposed improvements to advance our methodology include expanding AI prompting methods, integrating AI-assisted clustering to analyse stakeholder feedback, and validating the clusters through research that captures changes in perception patterns across time.

Taking a step further, our typology can guide future research studies in developing strategies that address the unique needs of this population. Resources like the playbook by Yuen et al. (2023) provide valuable context and guidance for applying these methods in future research. By having a shared understanding and addressing the evolving needs of an ageing population through collaborative, human-centred design, we believe that the new codesign and AI methodology and our typology contribute to theory development. Through systematic investigation, we can uncover perception patterns and inform future design work with human-centred insights, leading to the design of sustainable solutions at the early stages of ideation or concept generation (Siew et al., 2023). It supports future design researchers in capturing the nuanced social-emotional factors influencing technology adoption among seniors and understanding the practical applications and benefits of AI-powered research and practice. While more thought is needed in clustering analysis, meaningful engagement with seniors can help to construct the impact of ageing technology based on social-emotional factors within healthcare systems (e.g., hospitals, specialist clinics and treatment centres) and community health systems (e.g., social service agencies, grassroots organisations, social enterprises, private GPs operating in the heartlands).

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