Dynamic Evolution of Needs and Interaction Experiences in GenAI Health Video Co-Design Workshops for Older Adults: BERTopic-Based Analysis

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Abstract:

Background: Amid global aging, older adults' demand for health self-management is urgent. Generative AI (GenAI) offers personalized health support, and the quality of human-computer interaction (HCI) is crucial to its digital health participation. Existing research lacks a systematic analysis of HCI and co-design in dynamic GenAI scenarios. This study adopts BERTopic-based dynamic topic modeling to explore the evolutionary patterns of older adults' needs in three iterative GenAI health video co-design workshops, aiming to optimize HCI design of age-friendly GenAI health tools.

Methods: Twenty community-dwelling older adults (60-84 years) were recruited. Three rounds of iterative co-design workshops were conducted, collecting semi-structured interview records, focus group discussion transcripts, and user-GenAI interactive prompt texts. After text preprocessing, BERTopic dynamic topic modeling was used to analyze HCI-related topic distribution, core keywords, and semantic association changes across rounds.

Results: Four core HCI themes were identified through BERTopic modeling. Initial interactive exploration focused on basic operational demands for GenAI adaptation, including interface clarity and guided prompts. Interactive function adaptation shifted to personalization after basic mastery, such as adjustable voice speed and dialect support. In-depth interactive support emphasized health value, covering tailored advice interpretation and real-time health feedback. Persistent barriers centered on information reliability and privacy protection, which remained consistent across all rounds. A Sankey diagram visualized this transition, confirming privacy and reliability as the core trust determinant for participants.

Conclusion: Iterative co-design drove older adults' needs from basic operation to personalized experience and then to in-depth health value pursuit. Beyond verifying BERTopic's effectiveness in dynamic need analysis, the findings guide phased HCI design prioritizing simplicity early, personalization mid-term, and health value later, while requiring full-cycle privacy/reliability safeguards. This addresses the digital divide, facilitates GenAI health tool adoption among older adults, and supports aging society health management needs.

Keywords: Human-computer interaction (HCI); GenAI video; Older adults; Iterative workshop; Co-design; Dynamic topic modeling; BERTopic; Health self-management

1. Introduction

1.1 Research Background

Global population aging has become one of the most prominent social development trends in the 21st century. The World Health Organization (WHO) predicts that by 2050, the global population aged 65 and above will increase to 1.5 billion, accounting for a significant proportion of the total population (He et al. 2016). With aging, older adults face issues such as declining physical functions, sensory impairments, and memory loss, leading to an increasingly urgent need for disease prevention, health monitoring, and chronic disease management (Liu et al. 2022). Digital health technology, with its advantages of convenience, efficiency, and personalization, has become an important solution for older adults' health self-management (Liu, Luo, & Pang 2025). It enables older adults to access health resources promptly and improve the efficiency of health management.

However, older adults face multiple barriers in participating in digital health. Epidemiological data underscore the urgency of this issue: surveys indicate that approximately 40–60% of older adults in developed countries report limited digital literacy (Schreurs et al. 2017), and studies consistently find that 30–50% of older technology users experience technophobia, like anxiety or avoidance linked to new digital tools (Smrke et al. 2025). Trust concerns are equally prevalent, with over half of older adult respondents in health technology surveys expressing distrust of online health information (K. Rafiq et al. 2025). Existing studies have pointed out that older adults are not only limited by explicit barriers such as insufficient digital literacy and complex technical operations but also plagued by latent barriers, including psychological anxiety, information distrust, and unmet needs (Liu, Luo, Pang, et al. 2025). Traditional digital health tools are mostly designed with young users as prototypes, featuring complex interfaces and cumbersome operations that are difficult to adapt to older adults' cognitive and sensory characteristics (Wang et al. 2025). Meanwhile, older adults have a low acceptance of new technologies, generally suffering from "technophobia", worrying about operational errors leading to information leakage or equipment malfunctions (Smrke et al. 2025). This psychological barrier further hinders their use of digital health tools. In addition, the uneven quality of health information online and the problem of information overload make it difficult for older adults to distinguish the authenticity and reliability of information, exacerbating their distrust of digital health technologies (S. Rafiq et al. 2025).

The rapid development of GenAI has provided a new opportunity to address the above issues. GenAI can generate multi-modal content such as text, images, and videos on demand, and can customize health education content according to older adults' personal health conditions and educational backgrounds (Liu et al. 2026). For example, generating easy-to-understand health videos for common chronic diseases in older adults. Compared with traditional text or image-based health tools, GenAI-generated video content is intuitive, vivid, and easy to understand, which can make up for the decline in older adults' cognitive abilities and reduce the cognitive load of obtaining health information (Chen et al. 2025). GenAI supports dynamic content optimization and iterative updates, which can continuously adjust the form and difficulty of content according to user feedback, better adapting to older adults' usage needs (Hu & Shao 2025).

Collaborative design-oriented iterative user participation is the key to improving the age-friendliness of digital health tools (Duffy et al. 2025). This study used three consecutive GenAI health video co-design workshops, through a closed-loop of "generation-feedback-optimization", to deeply explore the real needs of older adults in health management, capture changes in their experiences and perceived barriers during technology use, and realize the joint creation of GenAI health tools by researchers and older adults. This immersive participation model not only helps optimize the functional design of GenAI tools but also enables older adults to gradually familiarize themselves with new technologies, alleviate technophobia, and enhance their enthusiasm for digital health participation. However, existing research has not systematically explored the evolutionary laws of older adults' needs, experiences, and barriers in consecutive iterative GenAI co-design workshops, nor has it adopted effective analytical methods to capture the semantic changes and thematic migration in the collaborative design process.

1.2 Research Gaps

Although GenAI shows great potential in the field of digital health, and iterative design has been proven to be an effective way to improve the acceptance of age-friendly technologies, there are still three key gaps in current research:

Firstly, there is a lack of dynamic analysis of the evolution of older adults' needs in consecutive iterative GenAI co-design workshops. Existing research mostly focuses on static feedback from older adults on GenAI tools after a single intervention, ignoring that as the depth of collaborative participation increases, older adults' needs may evolve from basic technology exploration to higher-level demands such as personalized functions and information authority. This static analysis makes it difficult to reveal the internal logic of demand evolution, resulting in a lack of targeting in the iterative optimization of GenAI tools.

Secondly, the application of BERTopic in capturing semantic changes in iterative collaborative design health technology research is insufficient. Existing research mostly uses traditional thematic analysis or a single Natural Language Processing (NLP) model, such as Latent Dirichlet Allocation (LDA) to analyze feedback data from older adults. These methods are difficult to accurately capture the subtle changes and semantic associations of topics in the collaborative design iteration process, primarily because LDA relies on a bag-of-words representation that ignores word order and contextual meaning, making it insensitive to the semantic drift that occurs as user needs evolve across iterative rounds (Jalsborn & Luotonen 2011; Onan et al. 2017; Zhuang et al. 2017). As a Transformer-based topic modeling method, BERTopic has strong deep semantic extraction capabilities and can effectively identify dynamically evolving topic structures. However, it has not been systematically applied in research on older adults' iterative digital health participation from the perspective of collaborative design.

Thirdly, the exploration of the mechanism by which iterative co-design alleviates older adults' digital health barriers is insufficient. Although existing research has identified various barriers faced by older adults, it has not deeply analyzed how iterative workshops can gradually alleviate these barriers through demand feedback and tool optimization in the collaborative design process, especially the alleviation path of latent barriers such as psychological anxiety and information distrust is not clear. This leads to the lack of consideration of the barrier alleviation mechanism in the design of age-friendly digital health tools, making it difficult to fundamentally improve older adults' digital health participation.

1.3 Research Questions

Based on the above research background and gaps, this study aims to systematically analyze the evolution of older adults' needs and barrier changes in three consecutive iterative GenAI health video co-design workshops through BERTopic dynamic topic modeling. The specific research questions are as follows:

1. How do older adults' need, experiences, and focus areas evolve during three consecutive GenAI health video co-design workshops?
2. What persistent barriers do older adults face in the iterative co-design workshops, and how can they be specifically addressed through GenAI tool optimization and intervention strategies?

1.4 Research Contributions

The theoretical and practical contributions of this study are mainly reflected in the following two aspects:

Firstly, the evolutionary laws of older adults' need for GenAI health tools are revealed. Through the design of three consecutive iterative co-design workshops, this study systematically presents the three-stage evolutionary path of older adults' needs from technical exploration to functional adaptation and then to decision support, clarifying the core needs and focus areas of each stage. This finding enriches the theory of older adults' acceptance of digital technology and provides a new perspective for understanding the acceptance process of new technologies.

Secondly, empirical evidence is provided for the iterative development of age-friendly digital health technologies from the perspective of co-design. This study identifies the persistent barriers of older adults in the iterative process and proposes targeted tool optimization suggestions and intervention strategies based on the laws of demand evolution, such as simplifying the operation interface, strengthening information authority verification, and providing personalized health plans. These suggestions can help developers better grasp the real needs of older adults, improve the age-friendliness of GenAI health tools, and promote the inclusiveness and sustainability of older adults' digital health participation.

2. Related Work

2.1 Older Adults' Digital Health Participation and Barriers

Older adults' digital health participation refers to behaviors such as older adults obtaining health information, using health management tools, and participating in online health services through digital technology (Li et al. 2025). Its core goal is to improve health self-management capabilities and quality of life (Polak et al. 2025). Older adults generally lack basic digital skills and are unable to operate smartphones or computers, resulting in ineffective use of digital health tools (Haase et al. 2025); some older adults are excluded from the digital health system due to economic constraints, lacking the necessary smart devices and network services (Hepburn et al. 2025).

The barriers of older adults mainly originate from psychological, cognitive, and social levels, with the characteristics of concealment and complexity, which are difficult to alleviate through simple technical training or equipment donations (Bertolazzi et al. 2024). Psychological barriers are mainly manifested as "technophobia" and low self-efficacy (Liu, Luo, Pang, et al. 2025). Older adults are resistant to digital health technology due to fear of operational errors, information leakage, or online fraud; at the same time, they generally believe that their learning ability has declined, and it is difficult to master new technologies (Ezeudoka & Fan 2024). This low self-efficacy further reduces their willingness to use digital health tools. Cognitive barriers mainly include information overload, insufficient information discrimination ability, and high cognitive load (Guo et al. 2025). There is a large amount of health information online with complex sources, making it difficult for older adults to screen effective information related to their own needs (Zhao et al. 2022). They cannot also distinguish false information and are easily misled (Zhou et al. 2023); the complex interfaces and professional terms of digital health tools also increase the cognitive load of older adults, making it difficult for them to understand and use (Kremer et al. 2022). Social barriers mainly involve insufficient social support and poor intergenerational communication (Van Gasse & Wyninckx 2024). When older adults encounter problems using digital health tools, they often struggle to obtain timely technical support. Additionally, the digital divide between the younger generation and older adults hinders the effective transmission of health information between generations (Kaihlanen et al. 2022).

Iterative design based on co-participation is considered an effective strategy to alleviate older adults' digital health barriers. Through multiple cycles of user feedback and tool optimization, it can gradually simplify the operation process, optimize the interface design, and improve the appropriateness of content, thereby reducing the impact of barriers (Azadi & García-Peñalvo 2025). The iterative collaborative participation process can enable older adults to familiarize themselves with new technologies gradually, accumulate use experience, improve self-efficacy, and alleviate technophobia (Kopeć et al. 2018). However, existing research has not fully explored how iterative collaborative design alleviates latent barriers, especially the lack of in-depth analysis of the alleviation mechanism of psychological and cognitive barriers.

2.2 Application of GenAI in the Field of Elderly Health

As an important branch of AI, GenAI has attracted increasing attention in the field of elderly health due to its powerful content generation capabilities. Currently, the application of GenAI in the field of elderly health mainly focuses on three aspects: health knowledge dissemination, personalized health management, and mental health support. In terms of health knowledge dissemination, GenAI can generate easy-to-understand health education content, such as prevention and management videos for common chronic diseases in older adults and healthy diet guidelines (Kush 2025). Compared with traditional health knowledge dissemination methods, GenAI-generated multi-modal content is more in line with older adults' cognitive characteristics and can improve the understandability and acceptance of health knowledge (Liu et al.). For example, GenAI can convert complex medical terms into daily language according to older adults' educational backgrounds and health conditions, combined with vivid animations and scenario demonstrations to help older adults better understand health knowledge (Choudhury & Roy 2026).

In terms of personalized health management, GenAI can generate personalized health management plans, such as exercise plans, diet suggestions, and medication reminders according to older adults' health data, such as age, health status, and living habits (Kumar 2024; Sharma & Sharma 2025). By continuously collecting older adults' health feedback, GenAI can dynamically adjust health management plans to ensure their targeting and effectiveness (Chatterjee et al. 2024). For example, for older adults with hypertension, GenAI can adjust the suggested salt intake and exercise intensity in the diet according to their blood pressure monitoring data (Rodriguez et al. 2024); for older adults with poor sleep quality, GenAI can generate personalized sleep improvement plans, including pre-sleep activity suggestions and sleep environment optimization (Nakari & Takadama 2024). In terms of mental health support, GenAI can simulate human conversations to provide emotional companionship and psychological counseling services for older adults. With the increase in the number of elderly living alone, loneliness has become an important factor affecting older adults' mental health. Chatbots driven by GenAI can conduct daily conversations with older adults, listen to their troubles and needs, and provide emotional support and psychological comfort (Nakari & Takadama 2024).

However, there are still many limitations in the application of GenAI in the field of elderly health. Firstly, existing GenAI tools lack age-friendly design, with complex interfaces and cumbersome operations that are difficult to adapt to older adults' usage needs (Deshpande & Kelkar 2025); secondly, there is a risk of inaccuracy in health content generated by GenAI, which may produce false information or unscientific health suggestions, posing potential threats to older adults' health (Bennani 2024); finally, privacy and security issues are one of the main concerns for older adults in using GenAI health tools (Khan et al. 2024). Older adults worry that their personal health information may be leaked or misused, which affects their acceptance of GenAI tools.

2.3 Application of BERTopic in Thematic Evolution Analysis

Topic modeling is one of the core methods of text data analysis, aiming to identify potential topic structures from a large amount of text data and reveal the core content and semantic associations of the text(Albalawi et al. 2020). Traditional topic modeling methods, such as LDA assume that documents are generated by mixing multiple topics, and can identify the main topics in the text. However, they have shortcomings in processing deep semantics and dynamically evolving topics (Jelodar et al. 2019). LDA relies on the bag-of-words model, making it difficult to capture the semantic associations between words (Zhuang et al. 2017). It is also sensitive to data preprocessing and parameter settings, and the effect is not good when analyzing short texts or texts with complex semantics (Onan et al. 2016; Wei et al. 2025).

BERTopic is a topic modeling method based on the Transformer model (Gottumukkala et al. 2025). By integrating BERT embedding technology and clustering algorithms, it significantly improves the accuracy and depth of topic recognition (George & Sumathy 2023). Compared with traditional topic modeling methods, BERTopic has the following advantages: Firstly, BERTopic uses Sentence-BERT to generate semantic embedding vectors of documents, which can capture the deep semantic associations between words and better identify semantically similar topics (Alsulami 2025); Secondly, BERTopic integrates UMAP dimensionality reduction algorithm and HDBSCAN clustering algorithm, which can effectively process high-dimensional semantic data and identify topic clusters with uneven density (Alqurashi & Ahmad 2024); Thirdly, BERTopic extracts topic keywords through the c-TF-IDF algorithm, which can accurately reflect the core content of each topic and improve the interpretability of the topic (Grootendorst 2022).

In recent years, BERTopic has been widely used in text data analysis in the health field, such as patient feedback analysis, health information mining, and medical dispute text processing (Li & Hu 2025). In research on older adults' digital health, BERTopic can effectively analyze data such as older adults' interview records and feedback texts, and identify their needs, barriers, and experiences in digital health participation (Chung et al. 2025). However, existing research mostly uses BERTopic for static topic analysis and has not applied it to dynamic thematic evolution research. In iterative digital health research, older adults' needs and barriers will change with the participation process. BERTopic's dynamic topic tracking capability can effectively capture this change, reveal the laws and trends of thematic evolution, and provide data support for iterative tool optimization.

2.4 Iterative Design, Co-Design, and Age-Friendly Technology Development

Iterative design is a user-centered approach that refines products or services through a cyclic "design-test-feedback-optimization" process (Smith 2018). In age-friendly technology development, it enables developers to deeply grasp older adults' real needs and usage habits, address pain points in technology use, and enhance age-friendliness. The core of iterative design lies in user feedback through multiple rounds of testing and feedback integration, interface layouts, operation flows, and functional settings are continuously optimized to align with older adults' cognitive and physical characteristics (Nielsen 2002).

Existing research has verified the effectiveness of iterative design in age-friendly technology. For instance, in age-adapted smartphone apps, multiple iterative tests simplify interface layouts, enlarge fonts, and streamline operations based on older adults' feedback (Jansen-Kosterink et al. 2019). However, traditional iterative design has limitations: feedback collection relies heavily on structured questionnaires and interviews, failing to capture implicit needs; manual coding and qualitative analysis of feedback lack scientific rigor and efficiency; and long iterative cycles struggle to respond to dynamic demand changes (Ganuga & Jilla 2018). The integration of co-design and BERTopic dynamic analysis addresses these gaps, enhancing the precision and efficiency of iterative development.

Co-design emphasizes equal participation of users (older adults) and developers throughout the design process, positioning older adults as "co-creators" rather than passive testers. This approach aligns with the collaborative nature of the GenAI health video workshops in this study, where older adults actively contribute to demand definition, prompt refinement, and video optimization. Unlike one-way feedback in traditional iterative design, co-design fosters bidirectional communication: older adults share lived experiences, implicit needs, and contextual usage scenarios, while developers translate these insights into technical solutions. For example, in the workshops, older adults proposed personalized adjustments and authority verification requirements through direct collaboration with researchers, ensuring the GenAI prototype (AIHealthV) reflects real-world usage needs.

3. Research Methods

3.1 Ethics Approval

This study has been approved by the Human Ethics Committee of Macao Polytechnic University (Approval No.: HEA006-FCA-2025), and all research procedures comply with the relevant guidelines of the Declaration of Helsinki. Before the start of the study, researchers fully explained the research purpose, research process, data collection methods, privacy protection measures, and the rights and obligations of participants to all potential participants, including voluntary participation, the right to withdraw at any time without any responsibility, and no impact on their rights and interests after withdrawal.

Participants were required to sign an offline paper-based “Free and Informed Consent Form”, which clearly informed participants that the research data would only be used for academic research, and all personal information would be anonymized to ensure that their identities would not be identified. To ensure data security, all collected text data, audio recordings, and other materials are stored on a password-protected encrypted server, and only authorized researchers can access them. In addition, to ensure the accuracy and security of GenAI-generated content, community health service center staff were invited to participate in the workshops to review the medical accuracy of the health videos generated in each round, preventing misleading information from causing adverse effects on participants. Before the workshops, researchers also clearly informed participants that “AI-generated content should be used in conjunction with professional medical advice”, informed them of the limitations of GenAI and the potential risk of inaccurate information, and guided participants to view AI-generated health information rationally.

3.2 Research Object Recruitment

The research objects of this study are community-dwelling older adults aged 60 and above in Macao. The recruitment work was completed with the assistance of community partners through a combination of offline poster promotion and community recommendations. The inclusion criteria for the research objects are as follows: (1) Aged 60 years or above; (2) Possessing basic smart device (such as smartphones, tablets) operation capabilities, and being able to perform simple interface clicks, text input, or voice input; (3) No prior experience in using GenAI-related tools to ensure that the research results are not affected by past usage experience; (4) Paying attention to their own health management and having the demand for obtaining health knowledge and improving health status; (5) Being able to communicate normally and understand the research process and the meaning of the questions; (6) Volunteering to participate in this study and signing the informed consent form.

Finally, 20 community-dwelling older adults were recruited to participate in the study. The sample covers different age groups, health statuses, living arrangements, and educational backgrounds to ensure the heterogeneity of the sample and the representativeness of the research results. The age range of the participants is 60-84 years, with an average age of 70.15 years; among them, 16 are females and 4 are males; their health status includes healthy, mild illness, and chronic diseases, among which 65% are chronic disease patients; their living arrangements are divided into living alone (40%) and living with family (60%); their educational backgrounds range from primary school to university, covering older adults with different knowledge levels. The health topics concerned by the participants are diverse, including hypertension, hyperlipidemia, hyperglycemia, joint health, sleep disorders, healthy diet, exercise and fitness, etc., which are highly consistent with the common health needs of older adults.

3.3 Design of Three Consecutive Iterative Co-Design Workshops

This study adopts a design of three consecutive iterative co-design workshops. Each round of workshops was carried out simultaneously for 20 participants, with each participant spending about 1 hour per round. The three rounds of workshops were conducted consecutively, forming a closed-loop of "generation-feedback-optimization". The core goal of the workshops is to realize the joint creation of GenAI health videos by participants and researchers through the in-depth participation of participants, gradually optimize the content and form of GenAI health videos, and at the same time capture the dynamic changes of participants' needs and experiences. The specific process of each round of workshops is as follows:

First round (initial interactive exploration stage): Firstly, researchers introduced the basic principles of GenAI, the generation process of health videos, and the overall arrangement of the workshops to participants, which lasted about 15 minutes. Subsequently, participants determined health topics of interest based on their own health status and needs, and put forward initial health information needs, such as "I want to understand the daily prevention methods of hypertension" and "How to improve diabetes through diet". Researchers and participants collaborated to convert these needs into prompt texts (Prompt) recognizable by GenAI, which were submitted to the GenAI video generation prototype tool (AIHealthV) to generate the first version of health videos. Finally, after watching the first version of the videos, participants shared their preliminary feedback on the accuracy of the video content, rationality of the form, and understandability of the language. Researchers and participants jointly discussed the feedback, laying the foundation for the video optimization in the second round of workshops.

Second round (interactive function adaptation stage): Researchers first fed back the optimization direction of the first round of videos to participants based on the collaborative discussion results of the previous round. Then, participants put forward more specific personalized needs and optimization suggestions based on the usage experience of the first round of videos, such as "I hope the video can adjust the diet suggestions according to my diabetes situation", "The font is too small, can it be made larger", and "The video content is too complex, I hope it can be more concise and clear". Researchers and participants collaborated to refine and adjust the prompt texts, and submitted them to AIHealthV again to generate a revised version of the videos. After watching the revised version of the videos, participants further provided optimization opinions, focusing on the satisfaction of personalized needs and the improvement of usage experience, and carried out in-depth collaborative discussion with researchers.

Third round (in-depth interactive support stage): Participants put forward more in-depth needs combined with the video experience of the previous two rounds, such as "I hope the health suggestions in the video have been reviewed by doctors", "I need a detailed weekly exercise plan from the video", and "I want to understand the advantages and disadvantages of traditional Chinese medicine and Western medicine in the treatment of osteoporosis".

Researchers and participants collaborated to convert these needs into more accurate prompt texts, integrating elements such as expert verification and executable plans, and generating the final version of the videos. In this round, the AIHealthV system was configured to generate videos structured around three components: (1) a medical accuracy preamble verified by community health staff and explicitly labeled as “Reviewed by Health Professional” within the video; (2) a personalized health action plan displayed as step-by-step on-screen text with accompanying voice narration, tailored to the participant’s specific chronic condition (e.g., a weekly low-impact exercise schedule for a participant with knee osteoarthritis); and (3) a summary Q&A panel addressing the top three concerns expressed in the previous round’s interviews. For example, participant E3 (68-year-old female, hypertension) received a video containing a 7-day sodium-reduced meal plan with portion guides alongside a warm-toned, large-font interface optimized from Round 2 feedback; participant E11 (75-year-old male, type 2 diabetes) received a video with a step-by-step morning exercise routine validated by a community physiotherapist. These concrete design choices illustrate how the iterative co-design process progressively moved from generic informational outputs to personalized, medically accountable health companions. After watching the final version of the videos, participants evaluated the overall satisfaction, information authority, and practicality of the videos, and shared their overall experience and persistent problems in the three rounds of co-design workshops.

In each round of workshops, community health service center staff conducted two rounds of medical accuracy reviews on the GenAI-generated videos: first, after the video script was generated, reviewing whether the health information in the script is scientific and accurate, and whether there is misleading content; second, after the final video rendering is completed, reviewing whether the audio and video content is consistent, and whether the information transmission is clear and accurate. Only the videos that have passed the review can be presented to participants to ensure the safety and reliability of the health information used in the workshops.

3.4 Data Collection

The data sources of this study mainly include three types of qualitative data: semi-structured interview records, focus group discussion data, and user prompt text records. All data are collected simultaneously during the workshops to ensure the authenticity and timeliness of the data.

Semi-structured interviews: After each round of workshops, one-on-one semi-structured interviews were conducted with each participant, lasting about 15 minutes. The interview outline was designed around the core content such as participants’ collaborative participation experience, demand expression, and concerns in this round of workshops. The main questions include: “Are you satisfied with the health video generated through collaborative design in this round? Why?”, “In the process of collaborating with researchers to optimize the video, what problems do you think exist?”, “What are you most worried about when using GenAI to generate health videos?”, “What other functions do you hope the GenAI health tool can provide through collaborative design?”. During the interview, researchers adopted an open-ended questioning method to encourage participants to fully express their true thoughts and feelings, and made detailed records. All interviews were recorded, and later transcribed into text data word by word, and the participants' information was anonymized, using "E1-E20" as the participants' codes.

Focus group discussions: After all, three rounds of workshops, a focus group discussion was organized, lasting about 40 minutes. All participants were invited to participate in the discussion around themes such as the overall experience of the three rounds of co-design workshops, demand evolution, and barrier changes. The discussion outline includes: "Compared with the first round, what changes have occurred in the needs you put forward in the third round? Why do you think such changes have occurred?", "In the process of collaborating with researchers to design GenAI health tools, what problems have not been solved?", "Do you think GenAI health tools designed through collaborative design are helpful for older adults' health self-management? Specifically reflected in which aspects?". The focus group discussion was hosted by two researchers, one responsible for guiding the discussion direction, asking questions, and interacting, and the other responsible for recording the discussion content and participants' non-verbal behaviors. The discussion process was fully recorded and later transcribed into text data and anonymized.

User prompt text records: In each round of workshops, after the participants put forward health needs, the prompt texts converted through collaborative discussion between researchers and participants were recorded in detail. The prompt text records include information such as participant codes, rounds, original demand descriptions, and optimized prompt text content, which fully reflect the transformation process of participants' needs from original expression to GenAI-recognizable format, and the refinement and deepening trajectory of needs in the three rounds of iterations.

3.5 Data Preprocessing

To ensure compatibility with BERTopic's semantic analysis capabilities (optimized for English language models) and maintain consistency with international research standards, the Chinese-language qualitative data (interview transcripts, focus group discussions, and prompt texts) underwent a systematic translation and preprocessing workflow. This two-stage process (translation + preprocessing) ensured data integrity, reduced language bias, and enhanced the model's ability to capture latent thematic patterns.

3.5.1 Translation Protocol

Given the colloquial and context-rich nature of older adults' expressions (including Cantonese dialect idioms and health-specific terminology), a rigorous translation approach was adopted to preserve semantic accuracy:

1. Bilingual Translation Team: Two bilingual researchers (fluent in Mandarin, Cantonese, and English) independently translated the Chinese text into English. One researcher specialized in gerontology, ensuring accurate conversion of health-related concepts and age-specific expressions; the other specialized in NLP, ensuring the translated text retained syntactic and semantic clarity for model analysis.
2. Back-Translation Validation: A third independent bilingual researcher performed back-translation (English → Chinese) of 20% of the translated corpus. Discrepancies between the original Chinese text and the back-translated text were resolved through

team discussions, focusing on preserving the original meaning, tone, and contextual nuances (e.g., hesitations, emotional expressions related to technophobia).

3. Terminology Standardization: A unified glossary was developed to standardize key terms across the translated corpus, including:
   a) Health conditions (e.g., “高血压” → “hypertension”, “糖尿病” → “diabetes mellitus”)
   b) Technological terms (e.g., “语音输入” → “voice input”, “字幕调节” → “subtitle adjustment”)
   c) Socio-psychological expressions (e.g., “怕用不好” → “fear of improper use”, “没人教” → “lack of guidance”)
4. Dialect Adaptation: Cantonese-specific expressions (e.g., “唔识操作” → “unable to operate”, “好复杂嘅” → “very complicated”) were translated to colloquial English that retained the original simplicity and emotional tone, avoiding overly formal language that might distort the participants’ intended meaning.

3.5.2 English Text Preprocessing

After translation validation, the English text dataset was preprocessed to remove noise and optimize it for BERTopic modeling. The steps were as follows:

1. Noise Removal: Elimination of non-semantic elements, including interviewer prompts (e.g., “Can you elaborate?”), filler words (e.g., “um”, “ah”), and redundant punctuation (e.g., multiple exclamation marks, ellipses).
2. Tokenization: Decomposition of text into individual words or phrases using the NLTK WordPunctTokenizer, which handles hyphenated terms (e.g., “user-friendly”) and contractions (e.g., “don’t” → “do not”) appropriately.
3. Lowercasing: Conversion of all text to lowercase to ensure consistency (e.g., “Privacy” and “privacy” were treated as the same term).
4. Stop Word Removal: Removal of English stop words (e.g., “the”, “and”, “is”) using the NLTK stopwords corpus, supplemented with domain-specific stop words (e.g., “workshop”, “video”) that appeared frequently but lacked thematic relevance.
5. Lemmatization: Reduction of words to their base forms using NLTK’s WordNetLemmatizer (e.g., “adjusting” → “adjust”, “worried” → “worry”) to reduce vocabulary redundancy while preserving semantic meaning.
6. Low-Frequency Word Filtering: Exclusion of words that appeared fewer than 3 times across the entire corpus to reduce noise (e.g., rare personal anecdotes, unique place names).
7. Text Segmentation: Division of long texts (e.g., focus group transcripts) into coherent segments (50–100 words) to maintain contextual integrity while ensuring the model could process the data efficiently.
8. The final preprocessed English text dataset was structured as a document-term matrix, with each document labeled by round (Round 1/Round 2/Round 3) and data type (interview/focus group/prompt text) to enable subsequent dynamic topic tracking.

3.6 BERTopic Dynamic Topic Modeling

3.6.1 Model Settings

The preprocessed English text data were analyzed using BERTopic to identify dynamic thematic patterns across the three workshop rounds. The model parameters were optimized for short-to-medium length texts (typical of older adults' feedback) and cross-round comparability:

1. Document Embedding: Sentence-BERT (all-MiniLM-L6-v2) was used to generate 384-dimensional semantic vectors for each document. This model was selected for its efficiency and ability to capture contextual meaning in short texts, which is critical for analyzing concise feedback from older adults. The core formula for embedding is based on the Transformer architecture's self-attention mechanism:
$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{Q \cdot K^{T}}{\sqrt{d_k}}\right) \cdot V$$
Where *Q (query)*, *K (key)*, and *V (value)* are input vector matrices, d_k is the dimension of query/key vectors, and the softmax function normalizes attention weights for an interpretable distribution.
2. Dimensionality Reduction: UMAP was applied to reduce the high-dimensional embedding vectors to 5 dimensions, balancing the preservation of local and global semantic structures. Parameters were set as $\mathrm{n\_neighbors} = 15, \mathrm{components} = 5, \text{and } \mathrm{metric} = '\mathrm{cosine}'$ to align with the characteristics of the translated text data. The choice of n_neighbors = 15 follows the recommendation in the original UMAP paper (McInnes et al. 2018) for medium-sized text corpora (100–500 documents): values below 10 over-emphasise local micro-structure and produce fragmented clusters, while values above 20 blur semantically distinct neighbourhoods. The target dimensionality of 5 components was selected through a preliminary grid search (testing 3, 5, 8, and 10 dimensions) by evaluating downstream cluster coherence; 5 dimensions consistently yielded the highest coherence scores while remaining computationally efficient. The cosine metric is the standard choice for high-dimensional text embeddings because it is scale-invariant and better captures directional semantic similarity than Euclidean distance (Pokropek 2024). The UMAP objective function is:
$$L = \Sigma\_(i < j)[d(x\_i, x\_j) \cdot \log(1 + e^{-\frac{\rho - a \cdot d(y_i, y_j) + b}{\sigma}} + \left(1 - d(x_i, x_j)\right) \cdot \log\left(1 + e^{-\frac{a \cdot d(y_i, y_j) - b - \rho}{\sigma}}\right]]$$
Where $d(x_i, x_j)$ is the distance between original data points, $d(y_i, y_j)$ is the distance between low-dimensional embedded points, and a, b, ρ, σ are hyperparameters optimized for text data.
3. Clustering: HDBSCAN was used for clustering, as it effectively identifies non-linear, density-varying clusters and handles noise (e.g., outliers in feedback). Parameters were set as $\mathrm{min\_cluster\_size{=}8}$ and $\mathrm{cluster\_selection\_method} = '\mathrm{eom}'$. The core formula for mutual reachability distance is:
$$\mathrm{reachability} - \mathrm{distance}_{k(a,b)} = \max\left(\mathrm{core} - \mathrm{distance}_{k(a)}, \mathrm{distance}(a, b)\right)$$
Where $\mathrm{core} - \mathrm{distance}_{k(a)}$ is the distance from point a to its k-th nearest neighbor,

and $\mathrm{distance}(a, b)$ is the Euclidean distance between points a and b. These parameter values were selected based on both published guidance and preliminary sensitivity analyses. For min_cluster_size = 8: HDBSCAN's original authors recommend setting this parameter to roughly the minimum number of semantically coherent data points that one would accept as a meaningful cluster (Campello et al. 2020; Campello et al. 2013, 2015); given our corpus of approximately 320 text segments across three rounds (about 107 per round), a value of 8 represents approximately 7.5% of a single round's data, consistent with best-practice recommendations for qualitative-scale text corpora (McInnes et al. 2018). Empirically, smaller values produced overly fragmented micro-clusters not interpretable as meaningful themes, while larger values merged semantically distinct topics, reducing sensitivity to the nuanced differences in older adults' needs across rounds. The 'eom' (Excess of Mass) cluster selection method was preferred over 'leaf' because it better preserves hierarchical cluster structure and is recommended for datasets where cluster density varies across topics (Campello et al. 2013). To verify topic stability, we ran the model with three alternative min_cluster_size values (6, 8, 10) and confirmed that the four core themes remained stable across all settings, with only minor variation in topic weight proportions (less than 5%), supporting the robustness of the identified thematic clusters.

4. Keyword Extraction: c-TF-IDF was employed to extract topic-specific keywords, normalizing term frequencies within topics to highlight meaningful terms. The formula is:

$$\mathrm{c-TF-IDF}(t, c) = \left[\frac{\mathrm{TF}(t, c)}{\Sigma_{(t' \in c) \mathrm{TF}(t', c)}}\right] \times \log\left(\frac{N}{\mathrm{DF}(t)}\right)$$

Where $\mathrm{TF}(t, c)$ is the term frequency of word t in topic c, $\Sigma_{(t' \in c) \mathrm{TF}(t', c)}$ is the total term frequency of all words in topic c, N is the total number of topics, and $\mathrm{DF}(t)$ is the number of topics containing word t. The top 10 keywords per topic were retained for thematic interpretation.

3.6.2 Dynamic Topic Tracking

To capture the evolution of older adults' needs, experiences, and barriers across the three iterative workshops, the BERTopic analysis was conducted in two phases: single-round topic identification and cross-round evolution comparison.

Single-Round Topic Identification: Separate BERTopic models were trained for each workshop round to identify round-specific core topics.

For each round, topic weight (proportion of documents assigned to the topic), document-level coherence, and keyword-level coherence were calculated to assess thematic significance and clarity.

Document-level coherence measures the tightness of semantic clustering within a topic:

$$\mathrm{Coherence}_{(\mathrm{doc})(c)} = \left[\frac{2}{m(m-1)}\right] \times \Sigma_{(i<j)\cos}(v_i, v_j)$$

Where m is the number of documents in topic c, and v_i, v_j are the semantic vectors of documents i and j.

Keyword-level coherence measures the semantic relevance of core keywords using pointwise mutual information (PMI):

$$\text{Coherence}_{(kw)(c)} = \left[\frac{1}{k(k-1)}\right] \times \Sigma_{(i<j)\log}\left(\frac{P(t_i, t_j) + \varepsilon}{P(t_i) \cdot P(t_j)}\right)$$

Where k is the number of core keywords in topic c, $P(t_i, t_j)$ is the co-occurrence probability of keywords t_i and t_j, $P(t_i) / P(t_j)$ are marginal probabilities, and Σ is a smoothing parameter.

Cross-Round Evolution Analysis: Topic Weight Change: Comparison of the weight of the same or semantically similar topics across rounds to reveal shifts in older adults' focus (e.g., from "privacy concerns" in Round 1 to "personalized content" in Round 2).

Keyword Replacement: Tracking of core keyword changes for evolving topics to capture the deepening of needs (e.g., from "simple to use" in Round 1 to "adjustable subtitle size" in Round 2).

Topic Similarity Calculation: Cosine similarity between topic vectors from different rounds to identify thematic inheritance, merging, or differentiation:

$$\text{Similarity}(c_1, c_2) = \cos(\mu_1, \mu_2) = (\mu_1 \cdot \mu_2)/($$

Where μ_1 and μ_2 are the average semantic vectors of topics from two different rounds, computed from the original 384-dimensional Sentence-BERT embeddings prior to UMAP dimensionality reduction, ensuring that topic vectors from all three rounds reside in the same semantic space.

Thematic Saturation Test: Saturation was confirmed when no new topics emerged in the third round's analysis. This was verified by comparing the topic structure of Round 3 with Rounds 1 and 2, ensuring that all core themes related to older adults' GenAI co-design experiences were captured.

Model Validity Verification:

- Expert Review: Two experts in gerontechnology and one expert in NLP evaluated the identified topics and their keywords, judging whether they accurately reflected the translated content and original participant intentions. The inter-expert agreement (Cohen's κ) was 0.83, indicating high validity.
- Translation Consistency Check: A random sample of 15% of the translated documents was re-evaluated to confirm that thematic patterns identified by BERTopic aligned with the original Chinese feedback, ensuring translation did not introduce thematic bias.

4. Results

4.1 Model Performance and Core Topic Identification

The BERTopic model demonstrated strong performance in capturing dynamic thematic patterns across the three workshop rounds, with document-level coherence scores increasing from 0.78 in Round 1 to 0.87 in Round 3, and keyword-level coherence scores rising from 0.62 to 0.75. This gradual improvement indicated that iterative co-design effectively enhanced the clarity and specificity of older adults' needs as they deepened their engagement with GenAI tools. A baseline LDA model was run on the same preprocessed corpus. To ensure a fair comparison, we conducted a grid search over the number of topics (k = 3–6) and hyperparameters ($\alpha \in \{0.05, 0.1\}$, $\beta \in \{0.01, 0.05\}$). The optimal configuration ($k = 4$, $\alpha = 0.1$, $\beta = 0.01$) was selected based on topic coherence. The LDA model achieved document-level coherence of 0.61-0.64 (vs. BERTopic's 0.78–0.87) and keyword-level coherence of 0.43-0.48 (vs. 0.62–0.75), confirming that BERTopic substantially outperforms LDA in extracting semantically coherent themes from this dataset. Crucially, LDA failed to distinguish the evolving nature of trust and privacy concerns across rounds, merging them with operational barriers into a single undifferentiated cluster, a distinction that BERTopic's contextual embeddings captured clearly. Through cross-round similarity analysis and expert validation, four core thematic clusters were identified as the most stable and interpretable, each showing distinct evolutionary trajectories while maintaining internal semantic consistency, confirming the model's ability to capture dynamic changes in needs and experiences.

4.2 Core Thematic Clusters and Evolutionary Trajectories

Table 1 presents the detailed characteristics of the four core thematic clusters identified by BERTopic. Note that Table 1 uses concise descriptive labels for each theme, while the Sankey diagram (Figure 1), word score chart (Figure 2), hierarchical clustering tree (Figure 3), and cosine similarity heatmap (Figure 4) employ abbreviated figure labels. The correspondence is: "Language support and interface adaptability" (Table 1) = "Multilingual Interaction & Interface Optimization" (Figures); "Targeted health management solutions" = "Chronic Disease & Sleep Health Management"; "Psychological and operational obstacles" = "Technology Acceptance & Operational Barriers"; and "Trust and data security demands" = "Information Reliability & Privacy Protection". The first theme, "Language support and interface adaptability", emerged as the most prominent with 31 entries, accounting for 47.0% of the total sample. This theme centers on older adults' demands for multilingual voice interaction, particularly Cantonese and interface optimization such as large fonts and warm colors, to accommodate their sensory and cognitive characteristics. Examples of participant feedback include requests for Cantonese voice interaction to enhance user-friendliness and enlarging font size to 18pt for better visibility, reflecting the critical role of basic usability in enabling older adults to engage with GenAI tools. The second theme, "Targeted health management solutions", includes 16 entries (24.2% of the sample) and focuses on personalized plans for chronic diseases like diabetes and hypertension, as well as sleep disorder management. Participants expressed needs for weekly exercise plans tailored to diabetes patients, sleep pattern analysis, and personalized insomnia improvement strategies, highlighting the practical, goal-driven nature of their engagement with digital health tools. "Psychological and operational obstacles" constitutes the third theme with 11 entries (16.7%), capturing psychological concerns such as fear of making mistakes and operational difficulties like complex login processes. Participants' feedback included worries about pressing the wrong buttons and frustration with password-based login systems that pose challenges for those with memory issues, underscoring the interplay between technical design and psychological acceptance. "Trust and data security demands", constitutes the fourth theme with 8 entries (12.1%). This theme reflects concerns about the authenticity of AI-generated health advice and the security of personal health data. Participants emphasized the need for health advice to be reviewed by professional doctors and expressed curiosity about where their health data is stored and who can access it, highlighting trust as a foundational prerequisite for sustained engagement with GenAI health tools.

Table 1. Topic Clustering Summary

Topic	Focus	Count	Description	Examples of prompt words for the classification topic
0	Language support and interface adaptability	31	Demand for multilingual voice interaction (e.g., Cantonese) and interface optimization (large font, warm colors) to match older adults' sensory and cognitive abilities.	"Cantonese voice interaction would be more user-friendly for older adults like me." "I hope to increase the font size to 18pt for better visibility."
1	Targeted health management solutions	16	Needs for personalized plans for chronic diseases (diabetes, hypertension) and sleep disorders, including diet guidance, exercise routines, and condition monitoring.	"I need AI to generate weekly exercise plans for diabetes patients." "AI should analyze my sleep patterns and provide personalized insomnia improvement plans."
2	Psychological and operational obstacles	11	Psychological concerns (fear of mistakes, unfamiliarity) and operational difficulties (complex login, steep learning curve) that affect older adults' AI tool adoption.	"I worry about pressing the wrong buttons and making mistakes." "The login process is too complicated for those with memory issues."
3	Trust and data security demands	8	Concerns about the authenticity of AI health advice (need for professional verification) and the security of personal health data (privacy settings, encryption).	"The health advice must be reviewed by professional doctors to ensure accuracy." "I want to know where my health data is stored and who can access it."

4.3 Dynamic Changes Across Rounds and Sankey Diagram Analysis

A Sankey diagram **Figure 1** was constructed to illustrate the dynamic evolution of HCI needs across the three workshops. **Figure 1** shows the sequential evolution of older adults' HCI needs, with clear linear flow of needs from "Basic Function Exploration" in Round 1 to "Usability & Personalization" in Round 2 and finally to "Health Decision Support" in Round 3. In Round 1, participants focused on basic interaction needs, including privacy, security, and operational simplicity, corresponding to the "Technology Acceptance & Operational Barriers" theme. By Round 2, participants shifted to personalized interface and interaction demands such as Cantonese voice support and large fonts, matching the “Multilingual Interaction & Interface Optimization” theme. In Round 3, participants prioritized health decision support, including chronic disease management and expert-verified advice, aligning with the “Chronic Disease & Sleep Health Management” theme. The flow volume in the Sankey diagram highlights the relative importance of each topic, with “Chronic Disease & Sleep Health Management” in Round 3 having the largest flow, indicating that older adults’ core expectation of GenAI tools is to address practical health problems. “Multilingual Interaction & Interface Optimization” in Round 2 showed significant flow, emphasizing that usability optimization is a prerequisite for deeper engagement, while “Technology Acceptance & Operational Barriers” and “Information Reliability & Privacy Protection” maintained consistent flow across rounds, confirming their role as foundational HCI elements.

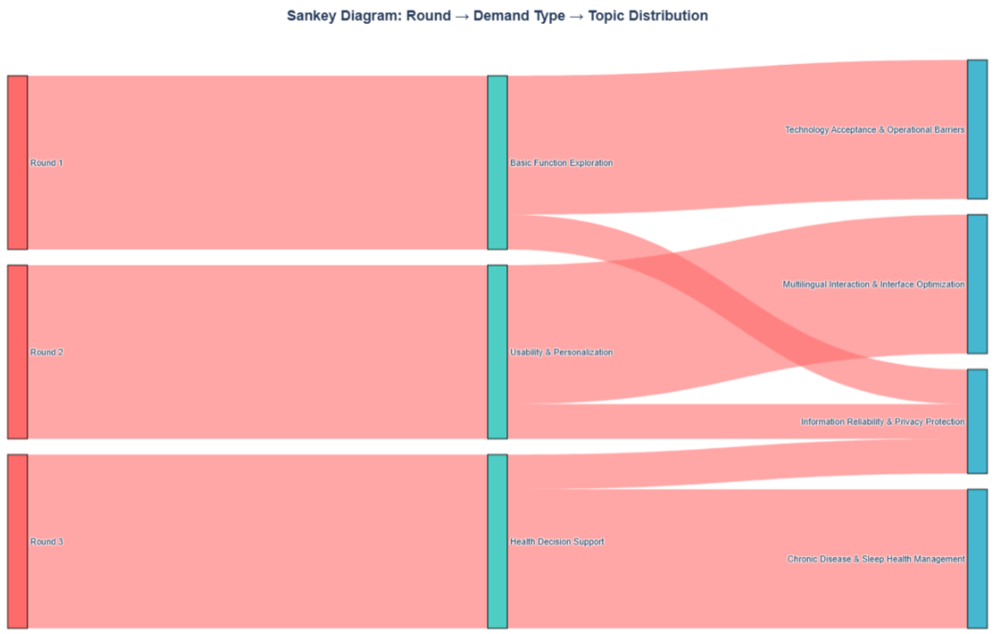

Figure 1. Sankey Diagram: Round → Demand Type → Topic Distribution.

The topic word scores in **Figure 2** clearly illustrate the keyword relevance characteristics of the four core themes. For the theme of Multilingual Interaction & Interface Optimization, keywords such as "voice", "hope", and "Cantonese" achieved high scores, directly reflecting users’ explicit demands for multilingual support, voice interaction, and a simplified interface. For the theme of Chronic Disease & Sleep Health Management, the core keywords "want", "information", and "advice" highlight users’ focus on accessing health information, professional advice, and disease management plans. The theme of Technology Acceptance & Operational Barriers features core keywords including "sleep", "exercise", and "need", which not only demonstrate users’ requirements for health behavior management but also imply operational challenges encountered during technology use. Meanwhile, in the theme of Information Reliability & Privacy Protection, dominant keywords such as "privacy", "data", and "security" underscore users’ high priority on data security and information authenticity.

The hierarchical clustering analysis in **Figure 3** further reveals the inherent relationships among the four themes: Multilingual Interaction & Interface Optimization and Technology Acceptance & Operational Barriers cluster together first, forming a "Usability Foundation" branch. This finding confirms that poor interface usability directly exacerbates users' psychological resistance to technology. Chronic Disease & Sleep Health Management and Information Reliability & Privacy Protection form a second branch focused on "Functional Value & Trust", indicating that once basic usability is ensured, users will pay greater attention to whether the tool can deliver tangible health benefits and whether it is sufficiently trustworthy. This clustering structure clearly reflects the sequential nature of older adults' needs: usability issues must be addressed first to enable users to engage with higher-level functional and trust-related demands.

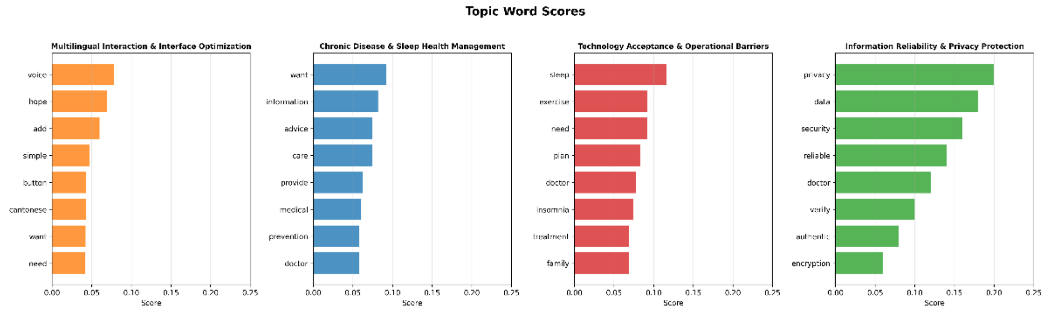

Figure 2. Topic Word Scores.

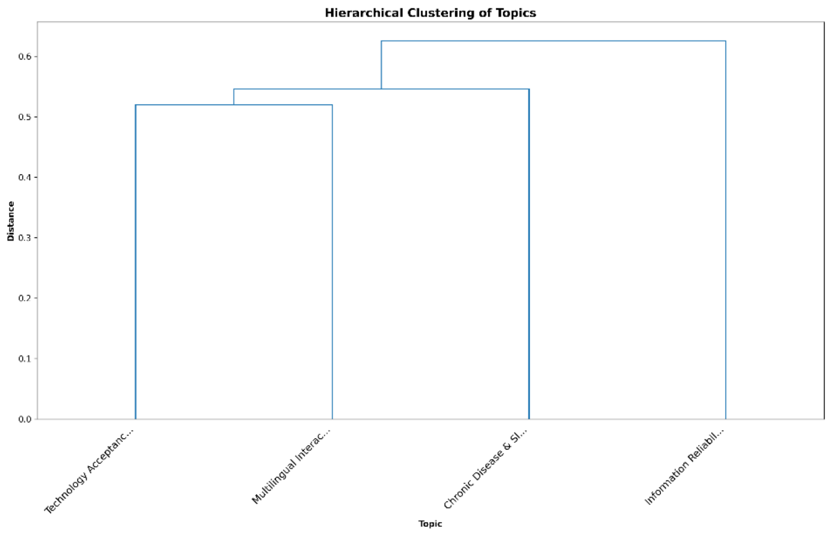

Figure 3. Hierarchical Clustering Tree.

4.4 Semantic Relationships

Figure 4 quantifies the semantic associations between the four themes using cosine similarity. Multilingual Interaction & Interface Optimization, as well as Technology Acceptance & Operational Barriers, exhibit the highest similarity (0.64), reinforcing the idea that intuitive interface design can help mitigate psychological and operational barriers to technology use. Chronic Disease & Sleep Health Management also shows a moderate similarity (0.62) with both Multilingual Interaction & Interface Optimization and Technology Acceptance & Operational Barriers, suggesting that usability is a prerequisite for participants to engage with health management functions fully. Notably, Information Reliability & Privacy Protection showed markedly lower semantic similarity with the remaining three themes (ranging from 0.12 to 0.18), indicating that trust and data security operate as a relatively independent dimension compared to the usability and health management clusters. This finding implies that even a highly usable tool with relevant health functions will fail to gain acceptance if participants do not trust its information or data security measures.

Figure 5 visualizes the core keywords of each theme through word clouds, offering deeper insight into the specific needs and concerns of older adults. The word cloud for Multilingual Interaction & Interface Optimization highlights “Cantonese”, “voice”, and “button” as its most prominent terms. This reflects not just a demand for multilingual support, but also a focus on accessible interaction modalities: voice input addresses potential motor or vision limitations, while simplified button layouts aim to reduce cognitive load for users with varying levels of digital literacy. Together, these keywords underscore a need for inclusive design that accommodates linguistic diversity and age-related functional challenges. For Chronic Disease & Sleep Health Management, the dominance of “sleep”, “exercise”, and “doctor” reveals a shift from passive information-seeking to active, actionable health management. These terms signal that older adults are not just looking for general health advice, but for personalized, goal-oriented plans, such as sleep improvement strategies or exercise regimens validated by medical professionals, which aligns with their desire for tangible health outcomes. The Technology Acceptance & Operational Barriers word cloud, featuring “need”, “plan”, and “insomnia”, goes beyond surface-level usability issues. It illustrates how psychological and practical challenges intersect: “need” and “plan” reflect the tension between users’ health goals and their ability to navigate the tool, while “insomnia” links operational friction directly to health outcomes, suggesting that poor usability can exacerbate existing health issues. Finally, the Information Reliability & Privacy Protection word cloud, with “privacy”, “data”, and “security” at its core, underscores a non-negotiable concern for older adults. These terms reveal that trust is not just an abstract concept but a foundational requirement: users need assurance that their sensitive health data is secure and that the information provided is authentic, as any perceived compromise in privacy or reliability can override even the most usable and functionally rich tool.

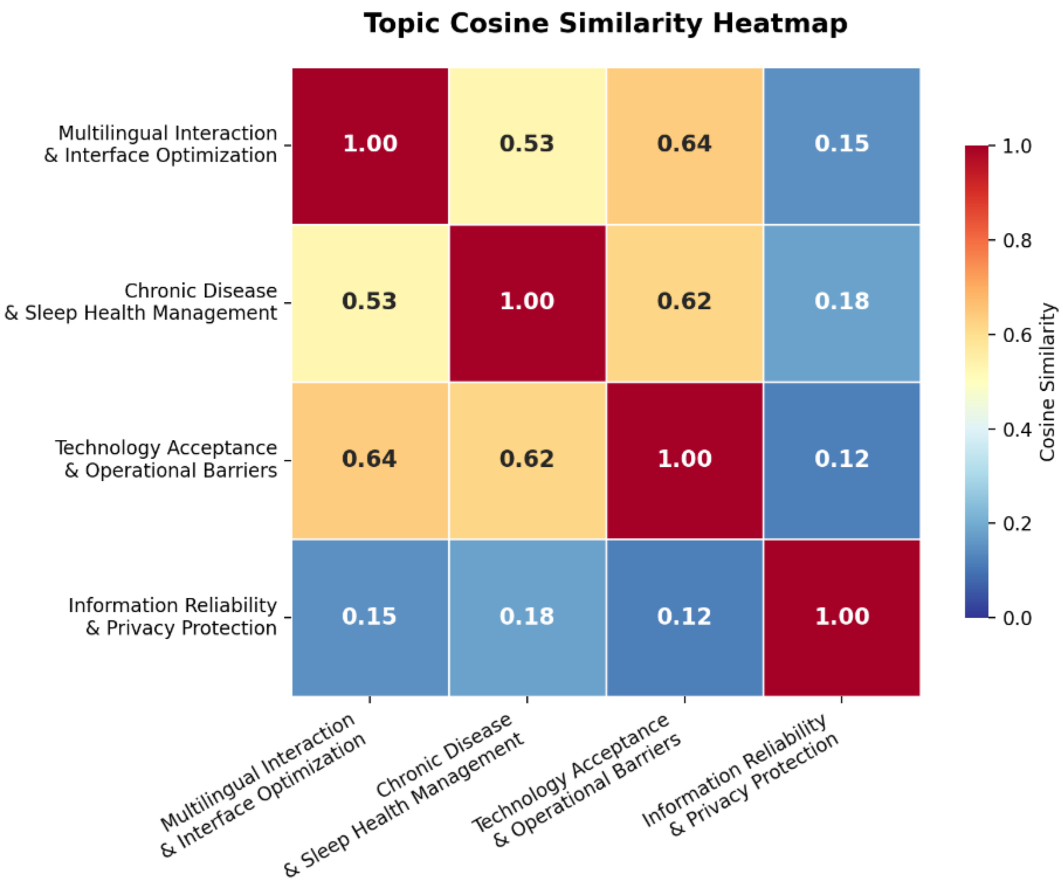

Figure 4. Topic Cosine Similarity Heatmap.

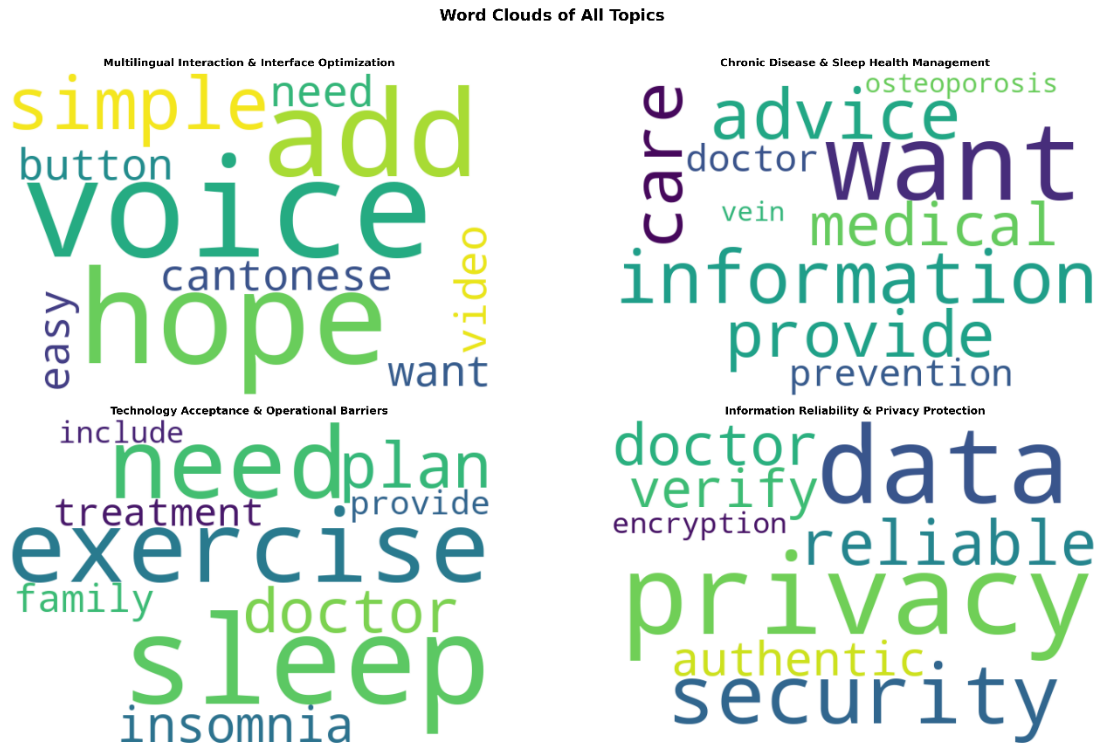

Figure 5. Word Clouds of All Topics.

4.5 Persistent Barriers and Unmet Needs

Analysis of cross-round feedback and thematic visualization, including the Sankey diagram, identified three persistent latent barriers that iterative optimization did not fully resolve. Psychological anxiety remained prevalent, the participants still expressing fear of technological mistakes despite simplified interfaces, particularly regarding data input and function switching. Representative examples illustrate the depth of these concerns: participant E7 stated, "Even though the buttons are larger now, I am still scared I might accidentally send my health data somewhere", and participant E14 confided, "I watched the video three times but still worry I will break something if I try it alone at home." These reactions reflect a pattern of technology-related anxiety grounded not simply in unfamiliarity but in a deeper sense of vulnerability, rooted in fears of irreversible error, perceived loss of autonomy, and distrust of systems perceived as opaque. Such responses align with established models of technophobia in aging populations, where psychological resistance often outlasts usability improvements (Smrke et al. 2025). This suggests that psychological barriers are not purely technical but rooted in long-standing attitudes toward new technology and cognitive changes associated with aging. Sensory and cognitive adaptation gaps persisted for participants with severe vision or memory decline, who reported that even optimized interfaces, such as enlarged fonts, remained challenging to navigate, highlighting the need for more personalized adaptive design beyond general adjustments. Additionally, participants emphasized the lack of continuous support beyond the workshop context, noting that temporary guidance during workshops did not address long-term usage needs, such as forgetting how to operate the tool weeks after participation, which points to a disconnect between short-term workshop interventions and the sustained support required for meaningful technology adoption. Addressing these persistent barriers requires support ecosystems that extend well beyond the tool itself. External mechanisms such as community digital literacy classes, caregiver-assisted onboarding programs, and family member training have demonstrated effectiveness in sustaining older adults' technology engagement over time (Cunningham et al. 2025). In the context of this study, participants who reported having a family member who helped them practice between sessions showed notably less anxiety by Round 3, suggesting that informal support networks can meaningfully complement structured co-design interventions. GenAI health tools should therefore be designed with this broader support ecology in mind. For example, by incorporating shareable tutorials for family caregivers and integration points with community health workers.

5. Discussion

5.1 The Sequential Nature of Older Adults' Needs Evolution

The findings of this study highlight a clear sequential trajectory in the evolution of older adults' needs when engaging with GenAI health tools through iterative co-design workshops. The initial focus on language support and interface adaptability, emerging as the most prominent theme, underscores that age-friendly design must prioritize foundational usability before addressing higher-level functions. This aligns with the Technology Acceptance Theory (TAM) (Davis 1989), where perceived ease of use is a primary driver of technology acceptance, but extends it by emphasizing the unique sensory and linguistic needs of older adults that are often overlooked in generic digital design. Older adults' demands for Cantonese voice interaction and large fonts are not trivial enhancements but essential enablers that allow them to engage with the tool at all, without which even the most sophisticated health management functions remain inaccessible. As participants gained familiarity with the tool, their needs evolved to focus on targeted health management solutions, reflecting a shift from "can I use it" to "does it help me manage my health". This transition highlights that older adults approach digital health tools with practical, goal-driven intentions; they are not seeking technology for novelty but to address specific health concerns like diabetes management or sleep disorders. The consistency of this theme across rounds further confirms the stability of these core health needs, emphasizing that GenAI tools must be designed with clear, purpose-driven functionality to resonate with older users. The final evolution toward trust and data security demands reveals a deeper layer of engagement: once participants confirmed the tool was usable and functional, they began to question its reliability and the safety of their personal data. This progression: usability → functionality → trust, mirrors the natural process of building confidence in new technology, particularly for a demographic that may be more cautious about digital innovations.

5.2 The Interplay Between Design, Psychology, and Trust

The high semantic similarity between language support and interface adaptability and psychological and operational obstacles underscores the intimate interplay between technical design and psychological acceptance (Patel 2024). Poorly designed interfaces, such as complex login processes or small fonts exacerbate feelings of anxiety and inadequacy, creating a cycle where technical barriers reinforce psychological resistance to technology (Timileyin 2024). Conversely, intuitive design can mitigate these psychological barriers: participants who praised the simplicity of voice interaction reported lower anxiety about making mistakes, demonstrating that design choices directly shape psychological responses (Wiklund 2005). This finding extends existing research on digital health barriers by showing that explicit technical and psychological barriers are not independent but mutually reinforcing, requiring a holistic design approach that addresses both simultaneously (Borges do Nascimento et al. 2023). Trust and data security demands, while an independent thematic cluster, interact with usability and functionality in shaping overall acceptance (Bhattacharya et al. 2024). Participants who trusted the tool's information, because it was verified by doctors, were more likely to engage with its health management functions, highlighting that trust acts as a catalyst for deeper engagement (Sillence et al. 2006). This aligns with the Health Belief Model (Orji et al. 2012), where perceived credibility of health information influences behavioral intentions. For older adults, who have witnessed the proliferation of misinformation online, trust is not an afterthought but a foundational prerequisite (Van der Linden 2023). The fact that trust-related demands persisted across all rounds means that it cannot be addressed through a single design feature but requires ongoing transparency, such as prominently displaying expert verification or data security policies and consistent delivery of accurate information.

5.3 HCI Implications: Designing for Needs in Aging Technology

The usability must serve as the foundational pillar of HCI design before users can meaningfully engage with higher-level functional and trust-related goals, so designers should prioritize inclusive interface solutions for the "Usability Foundation" branch (Murtezaj 2023). Such as integrating Cantonese voice prompts, large high-contrast buttons, and simplified navigation logic to mitigate cognitive and motor friction, addressing operational obstacles, e.g., complex workflows and psychological barriers, e.g., fear of errors, that hinder technology acceptance among older adults. Once basic usability is secured, HCI design should shift focus to the functional value and trust branch, embedding actionable, medically validated health features like personalized sleep improvement regimens and diabetes management trackers to deliver tangible value, while recognizing that information reliability and privacy protection operate as a non-negotiable parallel dimension in HCI, even highly usable and functionally robust tools will fail to gain sustained adoption if users lack confidence in data security, making transparent privacy controls and explicit verification mechanisms for building trust. These insights underscore the critical role of iterative co-design in HCI for aging technology, as treating user feedback as a dynamic, evolving dialogue, rather than a static snapshot allows designers to incrementally refine interfaces, first resolving usability pain points, then layering in functional depth, and continuously reinforcing trust ensuring digital health tools are not merely usable, but also meaningful, aligning with both immediate interaction needs and long-term health goals to foster sustained user engagement.

5.4 Digital Inclusion for Aging Populations

The findings of this study resonate within the broader context of digital inclusion for aging populations, highlighting that age-friendly technology design is not just about technical adjustments but about addressing the social and psychological factors that shape technology acceptance. The persistent psychological barriers and need for continuous support underscore that digital inclusion requires more than accessible tools, it requires a supportive ecosystem that includes community training, family involvement, and ongoing technical assistance. For example, community technology support centers could complement tool design by providing in-person guidance for older adults who struggle with even optimized interfaces, bridging the gap between short-term workshop interventions and long-term usage needs. Furthermore, the emphasis on language adaptability, particularly Cantonese, highlights the importance of cultural and linguistic inclusivity in digital health design. Many digital tools are designed with standard languages in mind, overlooking regional dialects that are central to communication for many older adults (Osborn & Osborn 2010). By incorporating dialect support, designers can make tools more accessible to diverse older populations, reducing linguistic barriers to digital health participation. This aligns with global efforts to promote health equity, recognizing that digital inclusion must address not just age-related barriers but also cultural and linguistic diversity (Cunningham et al. 2025). From a policy perspective, the findings support the need for regulations and initiatives that prioritize age-friendly design in digital health technologies. Governments and health authorities could establish age-friendly design standards that mandate basic usability features like multilingual support, large fonts, and clear data security policies. Additionally, funding for community-based digital literacy programs could complement tool design by equipping older adults with the skills and confidence to engage with digital health tools, addressing both technical and psychological barriers to adoption.

5.5 Implications for Age-Friendly GenAI Design

In the initial exploration phase, designers should prioritize language adaptability, including regional dialects and interface simplicity, such as one-click operations and large, high-contrast fonts. These features address the most immediate barriers to entry, enabling older adults to interact with the tool without feeling overwhelmed. Additionally, early design should incorporate trust-building elements such as clear statements about data encryption and expert review of content, to address initial distrust before it becomes a barrier to engagement. In the functional adaptation phase, tools should integrate personalized health management features tailored to common chronic conditions and sleep disorders, including customizable exercise plans, diet suggestions, and sleep monitoring functions that align with older adults' specific health goals. Designers should avoid generic health content and instead enable users to input personal health information, such as diabetes status or sleep patterns to receive targeted recommendations, as this personalization not only enhances the tool's utility but also increases user investment, with participants more likely to continue using a tool that addresses their unique needs. In the in-depth support phase, tools should add high-level features such as integration with community health services, long-term health tracking, and access to professional consultations, transforming the tool from a standalone resource into a comprehensive health management companion that addresses the need for sustained, meaningful support. Additionally, designers should incorporate ongoing support mechanisms, such as in-app tutorials, community technical support, or family sharing features, to address persistent barriers related to long-term usage and knowledge retention.

5.6 Limitations and Future Directions

This study has several limitations that point to future research directions. The sample size of 20 participants, while sufficient for thematic analysis, limits statistical generalizability, and the focus on urban community-dwelling older adults may not capture the needs of rural or institutionalized populations with different resources and challenges. The Macao-specific cultural and linguistic context, particularly the emphasis on Cantonese dialect support, may limit direct generalizability to older adults in other regions where different languages, healthcare systems, and digital infrastructure prevail. This represents a significant geographical context limitation: the study was conducted entirely within Macao's urban community health setting, which has specific features, a predominantly Cantonese-speaking population, a relatively compact city-state with dense community infrastructure, and a universal public healthcare system, that may not generalise to older adults in mainland China, Southeast Asia, Western countries, or low- and middle-income settings where digital health infrastructure, cultural attitudes toward AI, and social support systems differ substantially. Rural older adults face compounded barriers including unreliable internet connectivity, fewer community support resources, and greater reliance on informal caregiving networks, all of which interact differently with digital health tools than the conditions present among urban Macao participants. Future research should specifically recruit rural-dwelling older adults and institutionalized populations to examine whether the sequential need evolution pattern, usability to functionality to trust, holds across settings, or whether different trajectories emerge in contexts of greater social isolation or resource constraint.

Future research should expand the sample size and geographic scope to include more diverse older adults, including those with limited access to smart devices or digital literacy training. Additionally, the study's focus on GenAI health videos means the findings may not be fully applicable to other types of digital health technologies, such as wearable devices or telemedicine platforms. Future research could explore the evolutionary patterns of needs in different digital health contexts to identify commonalities and context-specific differences.

The study did not measure the impact of the optimized GenAI tools on older adults' actual health outcomes, such as improved health knowledge or behavior change. Future research should incorporate quantitative indicators to evaluate the practical effect of iterative design on health outcomes, linking user experience to meaningful health benefits. Finally, the study focused on short-term evolution across three workshops, but the long-term adoption and adaptation of GenAI tools by older adults remain underexplored. Future longitudinal research could track participants' usage patterns and needs over months or years, examining how their relationship with the tool evolves and identifying factors that support sustained engagement, which would provide valuable insights into the long-term sustainability of age-friendly digital health interventions and inform the development of tools that can grow with users' changing needs.

Future longitudinal studies should examine three outcome domains identified as critical by participants in this study: (1) digital literacy gains, whether continued exposure to co-designed GenAI tools produces measurable improvements in older adults' ability to independently navigate digital health environments; (2) health behavior change, like personalized AI-generated health plans translate into adherence to exercise routines, dietary adjustments, or medication management; and (3) social connectedness, like tool features that involve family caregivers or community health workers reduce the social isolation that exacerbates health risks among older adults. Addressing these questions would substantially strengthen the evidence base for GenAI as a viable and scalable component of aging-in-place health support systems.

6. Conclusion

This study demonstrates that older adults' HCI needs in GenAI health tools evolve through a sequential trajectory, from language support and interface adaptability to targeted health management solutions, and finally to trust and data security demands shaped by iterative co-design workshops. The four core themes identified provide a comprehensive framework for age-friendly GenAI design, highlighting that usability, functionality, and trust are equally critical dimensions of HCI for older adults. The Sankey diagram further visualizes this sequential evolution, revealing the linear flow of demands and the persistent role of trust, which enhances the interpretability and practical relevance of the findings. This study emphasizes that digital inclusion for older adults is a multifaceted endeavor that requires collaboration between designers, researchers, communities, and families. By following the evolutionary trajectory of older adults' needs and addressing both explicit technical barriers and latent psychological and trust-related concerns, developers can create GenAI health tools that truly meet the needs of aging populations. In doing so, this research contributes to advancing health equity and promoting healthy aging in an increasingly digital world.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

The author confirms that all data generated or analyzed during this study are included in this published article. Furthermore, primary and secondary sources and data supporting the findings of this study were all publicly available at the time of submission.

Competing interests

The authors declare no competing interests.

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Authors' contributions

W.Z. and T.L. contributed equally to this work and should be considered co-first authors. W.Z. and T.L. proposed and designed this study. Y.L. helped with data analyses and resolved disagreements in the review process. W.Z. and T.L. wrote the manuscript with the assistance of Y.L. P.P. supervised and provided resources for this work. All authors discussed the results and contributed to the final manuscript.

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