Finding the Right Balance: User Control and Automation in AI Tools for Supporting Older Adults' Health Information Tasks

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Abstract

Older adults face unique challenges in maintaining independence while managing increasingly complex health information tasks in their home environment. AI-assisted tools have emerged as promising solutions to support these needs, yet determining the optimal balance between system automation and user agency remains a critical challenge. This paper investigates older adults' preferences regarding automation levels for different AI features supporting health information tasks. We developed a tablet-based prototype that explores various degrees of automation across these features, from fully automated to manual control and mixed-initiative approaches. Through focus group studies with nine older adults, we found that participants' desired level of automation varied significantly based on task characteristics and complexity. Based on these insights, we developed a classification framework categorizing features by preferred interaction approaches: full delegation, direct control, and collaborative completion, leading to design recommendations for balancing system capabilities with user agency in AI-assisted health information tools.

CCS Concepts

• **Human-centered computing** → **Empirical studies in HCI**; *Empirical studies in accessibility*; • **Social and professional topics** → Seniors; • **Applied computing** → Health care information systems.

Keywords

older adults, intelligent assistants, health information tasks, AI tools, mixed-initiative

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1 Introduction

Managing health information tasks at home can present unique challenges for older adults, who must navigate increasingly complex healthcare demands while maintaining independence [2, 25]. These tasks span multiple domains, from medication management and symptom tracking to understanding medical instructions and coordinating care plans [25]. CSCW and CHI researchers have begun introducing AI-enabled solutions to streamline and support these information management needs. Examples include voice chatbots for medication reminders, [16], AI assistants for health information seeking [10], and conversational agents for scaffolding care conversations [37]. However, a critical knowledge gap exists regarding the optimal level of automation in these AI-assisted tools for balancing needs for assistance and independence. Although full automation may reduce cognitive burden, it risks diminishing user engagement and agency in health management; conversely, minimal automation may preserve control but potentially fail to provide adequate support [20]. Given these trade-offs, understanding older adults' preferences regarding automation levels becomes crucial for designing effective AI tools for health information management. In this paper, we aim to answer the following research question: What are older adults' preferences for automation across different AI features - such as medical text simplification and health information seeking - when designing an AI-assisted tool to support their health information tasks at home?

To address this question, we developed a tablet-based prototype incorporating varying degrees of automation for health information tasks. The system ranges from fully automated features (AI-generated encounter notes from medical conversations) to user-controlled capabilities (customizable text summarization), allowing us to explore when and for what tasks older adults prefer direct control versus AI delegation.

Through two focus group studies with nine older adults, we examined their perceptions and interactions with the prototype's features. Participants' feedback revealed nuanced preferences regarding control and automation. For instance, rather than accepting fully automated medical text simplification, they preferred a manual control approach where they could look up specific term definitions as needed while reading the original text. From our findings, we developed a classification framework that categorizes features according to older adults' interaction preferences: full delegation, direct control, and collaborative completion. Our paper makes three main contributions: (1) a prototype demonstrating features with varying levels of automation versus user control for supporting older adults' health information tasks at home; (2) a framework derived from user studies that categorizes these features based on preferred interaction approaches (full delegation, direct control, collaborative completion); and (3) discussion and design implications for implementing appropriate levels of user involvement in AI-assisted health information tools.

2 Related Work

Due to increasing demands on the healthcare system, many care tasks are shifting to the home environment [12], where older adults, especially those with chronic conditions, engage in extensive "information work" to manage their long-term care [19]. To support these information tasks, intelligent assistants have emerged as promising tools for aging populations [27, 33, 43]. These systems assist with various activities, from navigating electronic health records [26] to managing medication schedules and health monitoring [16, 18]. However, adopting these technologies among older adults remains challenging, primarily due to concerns about user control and agency [4]. Studies show that commercial IAs, especially those without visual interfaces, often fail to provide sufficient control over information verification [5, 41]. This limitation is consistent with older adults' reported concerns about losing agency when using IAs for health-related tasks [29, 38]. Without visual feedback and adequate interaction options, users can feel disconnected from their health management process [7]. To address these issues, Horvitz suggests mixed-initiative or semi-automated interfaces as a solution, emphasizing the importance of matching system automation to user preferences [20].

Building on this mixed-initiative approach, researchers have explored IAs with visual interfaces, incorporating features like voice transcriptions and chatbots [21, 27] that allow users to leverage automation while having control over verifying information sources. Studies show that older adults value independently querying health information through chatbots [21] and controlling access to simplified doctor's notes through mobile applications [22, 23]. These findings demonstrate older adults' preference for semi-automated solutions that balance agency with automated assistance. However, we still lack an understanding of how to calibrate automation levels across different health information tasks for older adults—a critical gap given the varying complexity of tasks and potential differences in automation preferences. In this paper, we address this gap by investigating older adults' preferences for automation across different AI-enabled health information management features.

3 Health Information Prototype

Building upon existing literature on AI-assisted technologies to support older adults' health information tasks at home [8, 11, 16, 21], we developed a paper prototype that simulates voice and chat functionalities (see Figure 1). The prototype includes features with varying levels of automation to address three core design goals: 1) automated generation of medical notes from clinical conversations, 2) enhanced access to health information through AI-powered question answering, summarization, and text simplification, and 3) streamlined information sharing with stakeholders involved in the older adults' care team. Prior research has demonstrated that while older adults employ various methods to recall information from doctors' visits [30, 40, 42], many of these approaches prove inefficient and often require additional follow-up [15]. Our first design goal addresses this challenge by enabling older adults to easily capture and reference medical conversations independently without relying on caregivers, online search, or portals. Studies also show that after doctor visits, older adults often seek answers to additional health-related questions about their visits or medical conditions, which is crucial to their management of health information [9]. Therefore, our prototype included a question-answering feature to support health queries. In addition, older adults often struggle to understand complex medical terminology [3, 28], which motivated our inclusion of text simplification and summarization features. Finally, research indicates that older adults value the ability to share medical information with their formal and informal caregivers [22], leading to our third design goal of integrated information-sharing capabilities (See Appendix A for examples of prototype features).

To create realistic content for the paper prototype, we generated examples using the T5 model [36] for text summarization and question-answering, while we generated text simplification examples using the Rewordify platform (https://rewordify.com/index.php). To create representative medical documentation, we utilized the *Medical Transcriptions* dataset [6], which comprises 5,000 anonymized clinical notes. We manually selected sample notes from this dataset and leveraged the T5 model to categorize their content into three primary sections: history, medication, and exam.

4 Study Design

We conducted two in-person focus group studies with nine older adults (aged 60+) to investigate their preferences regarding automation levels across different prototype features and understand how to better balance user control with AI assistance. Our university's institutional review board approved the study protocol prior to data collection. We recruited participants through multiple channels, including word of mouth, brochures posted in senior centers, and email distributions. During recruitment, we also screened participants to ensure they had experience with intelligent assistants by asking questions such as "Are you familiar with intelligent assistants, such as Alexa?" We also assessed their likelihood of using such tools to ensure relevant experience to provide feedback on the designs. Following the screening process, we formed two focus groups: one with four participants and another with five participants. Table 1 summarizes participants' responses to screening questions.

We conducted focus groups at a senior center located in Indiana. At the beginning of the study, we collected demographic data. Seven participants identified as female and two as male. Participants' ages ranged from 60 to 86 (Avg=73.11, STD=2.39). Seven participants reported managing chronic illnesses, with four managing multiple conditions. These conditions included high blood pressure, aortic valve disease, diabetes, asthma, rheumatoid arthritis, acid reflux, pancreatitis, and degenerative disk disease. The duration of chronic illnesses varied among participants with five managing their conditions for more than 10 years, one for 4-10 years, and one for 2-4 years.

After collecting demographic information, we distributed the paper prototype providing each participant with a copy of the four-page design. We began with a comprehensive walkthrough

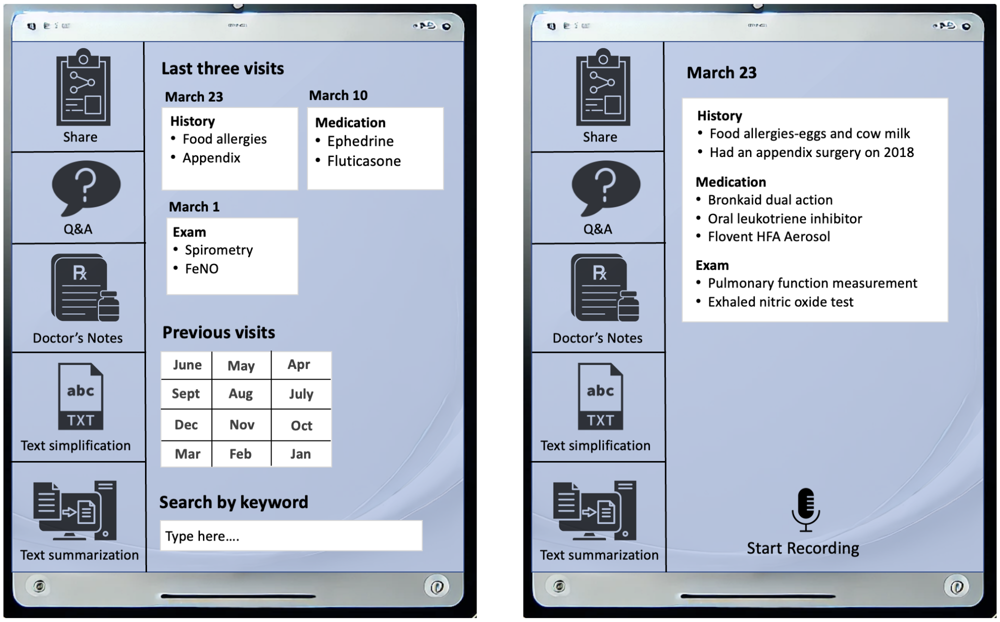

Figure 1: Paper prototype of a health assistant interface for older adults, displaying prior visits. The interface includes navigation options, such as text summarization and question answering.

explaining each feature, after which we gave participants time to independently explore the prototype and ask questions to clarify any design aspects. Afterward, we proceeded with the interview questions. Interview questions focused on four main areas: (1) participants' current strategies for managing health information at home after medical visits, (2) their experiences with and reactions to different prototype features, (3) situations where they would find each feature most helpful or challenging, and (4) ways they envision incorporating these features into their future health information management routines. Focus group sessions, each lasting approximately one hour, were audio recorded and transcribed with an automated audio transcription service. Each participant received a $35 gift card as compensation. One researcher conducted all the interviews and performed an open coding thematic analysis of participants' responses. The coding process involved two phases, and the research team discussed the results of each round until consensus was reached.

5 Findings

Our analysis revealed three distinct approaches to how participants preferred to manage their health information tasks when using the AI-assisted tool: full task delegation, direct task management, and collaborative task completion. Below, we present these approaches and discuss how participants' preferences varied across different types of tasks.

5.1 Full Task Delegation

For certain health information tasks, participants preferred full AI automation, viewing direct user involvement as unnecessary overhead that could be efficiently handled by the system.

5.1.1 Text Summarization. One feature of our prototype, text summarization, was initially implemented as a semi-automated approach, allowing users to control AI-generated summary length through a slider and setting minimum and maximum word counts. However, participants found this level of control overwhelming and potentially counterproductive. While they valued the potential of AI-assisted text summarization for medical content, they expressed that managing summary length manually created an unnecessary cognitive burden. Their primary concern was the challenge of determining the appropriate length while maintaining comprehensive information. As P1 explained: "*if you shorten it, maybe you won't have everything either. So, either you won't have everything, or you won't have to plow through a bunch of stuff.*" Therefore, instead of manual length control, participants preferred to fully delegate the summarization task to AI, trusting the system to determine an appropriate length to preserve essential information.

5.2 Direct Task Management

For certain health information tasks, participants strongly preferred maintaining direct control rather than delegating fully to AI assistance. This preference emerged particularly in tasks involving critical medical information understanding and decision-making, where participants emphasized the importance of user agency and trusted information sources.

5.2.1 Text Simplification and Term Understanding. When presented with examples of AI-simplified medical text, participants acknowledged its potential value, particularly for unfamiliar medical terminology. However, they expressed strong preferences for maintaining

Table 1: Screening Responses: Participants' Familiarity and Usage Patterns with Intelligent Assistants

Participant	Q1: Familiarity	Q2: Likelihood of Use	Current Usage Pattern
P1	Very familiar	Very likely	Daily use (Alexa) for reminders, weather updates
P2	Familiar	Likely	Several times/week (Alexa, Google Assistant)
P3	Very familiar	Very likely	Daily use (Alexa) for music, timers, news
P4	Somewhat familiar	Somewhat likely	Weekly use (Siri) for basic queries
P5	Familiar	Likely	Daily use (Google Assistant) for reminders, calls
P6	Very familiar	Very likely	Multiple times/day (Alexa, Siri) for various tasks
P7	Familiar	Likely	Several times/week (Alexa) for weather, music
P8	Somewhat familiar	Likely	Weekly use (Alexa) through family setup
P9	Very familiar	Very likely	Daily use (Google Assistant, Alexa) for home automation

direct control over their comprehension process. Their primary concern centered on the reliability of AI-generated simplifications and potential meaning alterations from the AI that could lead to misunderstandings. Instead of automated text simplification, participants proposed a user-directed approach. P2 suggested incorporating a search functionality: "*you'd have a search bar. And then you put in, you know when see a term you don't know. And if there's a, you know, a data in the background of these definitions, it could pull it up for you.*" This preference for a search-based approach reflects participants' desire to maintain agency in their learning process while receiving targeted support for specific terms they choose to investigate.

This preference for manual control was echoed by other participants who emphasized the importance of accessing verified medical sources. P4 elaborated on this approach: "*Somehow link it to a medical dictionary, maybe not have to do all of the, the input. But you know, if you could find something that could be used. That way, instead of simplify, you could find, you know, the definition of stuff you don't know.*" Participants believed that retrieving definitions from verified medical dictionaries, rather than relying on AI-generated simplifications, would enhance system trustworthiness and address their concerns about accuracy.

5.2.2 Health Information Source Selection. The prototype included a feature allowing users to ask open-ended health-related questions and view responses from various sources. Users could access the complete answer by selecting 'view entire answer' and had the flexibility to switch between different information sources. While participants appreciated the ability to query health information, they expressed strong preferences about source credibility and how they wanted to interact with different sources. Participants demonstrated clear judgment about source reliability, expressing trust in established medical resources while being skeptical of user-generated content. As P2 explained: "*Wiki[pedia] can be updated by anybody really, you know, pretty much. I don't think I'd use Wiki for medical.*" They specifically trusted sources such as WebMD, MedlinePlus, Harvard University, and doctor's notes. In addition, participants preferred a more focused approach to reviewing different sources. As P5 noted: "*I would like it better if you could just pick one source to view at a time and toggle between different sources, rather than seeing multiple sources at once.*" This preference for sequential review indicates participants' desire for a methodical approach to information verification, allowing them to carefully evaluate each source independently.

5.2.3 Care Network Communication. Participants were particularly impressed by the prototype's sharing features, emphasizing how its ability to share medical information with both formal and informal caregivers could substantially improve health information management at home. While the system automatically captured and organized medical information, participants appreciated maintaining control over what information to share, when to share it, and with whom to share it. They provided several examples of how this information-sharing approach could be useful. For instance, participants described scenarios where they returned home from medical visits and needed to communicate key information to family members who could not attend the appointment. Similarly, when managing multiple health conditions at home, participants noted how the tool could help them selectively share relevant information with different caregivers – for example, sharing medication updates with a spouse who helps manage daily medications while sending visit summaries to adult children who help coordinate care remotely. This selective sharing not only helps keep family members informed but also enables older adults to maintain independence while receiving necessary support. Participants wanted to maintain agency in the sharing process, suggesting additional control mechanisms such as email options for longer information and the ability to select specific portions of information to share with different caregivers.

5.3 Collaborative AI Task Completion

Participants appreciated AI assistance for some tasks while maintaining meaningful involvement, revealing opportunities for effective collaboration between users and AI, where neither full delegation nor complete user control was ideal.

5.3.1 Medical Conversation Documentation. Our prototype displayed users' three most recent medical visits. When users selected a visit, they could view a summary of their conversations with their physician, with doctor's notes automatically categorized into history, medication, and exam sections. Participants emphasized that while they valued these categorized summaries, they also wanted to retain access to the original audio recordings and complete transcripts. As P3 explained: "*a summary is going to pick out the highlights, but you might have questions about specific details that weren't included, like 'what exactly did she say about this?"* P4 agreed, noting that "*you might want to know something specific but forgot what the exact response was."* The need for complete records was further illustrated through specific scenarios, such as appointment scheduling discrepancies. P6 shared a recent experience: "*Like the other day, my doctor scheduled my visit. Instead of recording it as two or four weeks, it was entered as two months. If they could have gone back to listen to what he actually said, they would have scheduled the appointment correctly."* These experiences highlighted participants' preference for a collaborative approach, where AI handles the initial capture and organization while users maintain the ability to verify and access complete information when needed.

5.3.2 Search and Information Retrieval. The home page of our prototype allows participants to search for specific visits using keywords via the search bar at the bottom. Our participants mentioned that when searching for a keyword, they would like the system to complete their search by providing suggestions, which could expedite the process and improve the overall search experience. This preference indicates participants' desire for a semi-automated approach where AI provides intelligent suggestions while users maintain agency in selecting and refining their search terms. This enhancement would assist users in finding the exact information they seek, even if they are unsure of the precise terms or spelling. Moreover, we believe incorporating an adaptive suggestion mechanism that learns from user behavior over time would further refine the search suggestions and personalize the results to each user's preferences and needs.

6 Discussion

We conducted two focus group studies to investigate older adults' preferences regarding automation levels in AI-assisted health information tools. Our analysis revealed that participants' desired level of control varied by task characteristics. Based on these findings, we developed an initial framework for implementing different levels of automation. Below, we present this framework and its implications for designing effective AI-assisted health information tools for older adults.

6.1 Framework for Automation Preferences in Health Information Management

Our analysis of participants' interactions with the prototype revealed that the appropriate level of automation in health information management tools is highly context-dependent. Rather than preferring a uniform approach to automation, older adults expressed varying preferences based on each task's specific characteristics and requirements. These findings align with others suggesting that older adults' preferences for automated health information-management tools can vary due to concerns about accuracy, trust, and reliability in different scenarios [5, 7, 17, 21]. For example, Brewer found that when using automated assistants for health information seeking, older adults struggled to trust the information provided due to the lack of visual cues [7]. In their study, Harrington and Egede found that Black older adults raised concerns about the accuracy and credibility of answers returned for health chatbots [17]. Yet our findings also suggest that strategies such as providing access to original sources or providing control mechanisms can mitigate some of these concerns for certain tasks. Still, older adults' perceptions of the automated features in our prototype are likely shaped by the specific health scenarios explored. These nuanced preferences led us to develop an initial framework that categorizes features into three distinct approaches: full delegation, direct control, and collaborative completion. This framework can guide designers of similar technologies in determining appropriate levels of automation for different health information management features, ensuring that AI assistance enhances rather than diminishes older adults' sense of agency in managing their health information.

Our results indicate that participants preferred full delegation for routine, straightforward tasks where accuracy could be maintained without direct user oversight. For instance, in text summarization, participants trusted AI to determine appropriate summary lengths autonomously, viewing manual length control as an unnecessary burden. This preference for delegation emerged when the task was well-defined, and the consequences of potential errors were minimal. However, participants strongly preferred direct control for tasks involving medical comprehension and information verification that typically involve human decision-making or could be safety or privacy-critical. This was particularly evident in text simplification, where participants rejected automated simplification in favor of a user-directed approach for looking up specific terms. Similarly, in managing care network communication, participants wanted direct control over what information to share and with whom to share it. This preference for direct control was prominent when tasks involved critical medical information or required personal judgment. Finally, several features showed the value of collaborative completion between users and AI, where AI could improve efficiency without compromising safety or privacy and where humans could easily verify the results. For instance, in medical conversation documentation, while AI handled the initial capture and categorization of information, participants wanted the ability to review, edit, and access complete records. Similarly,

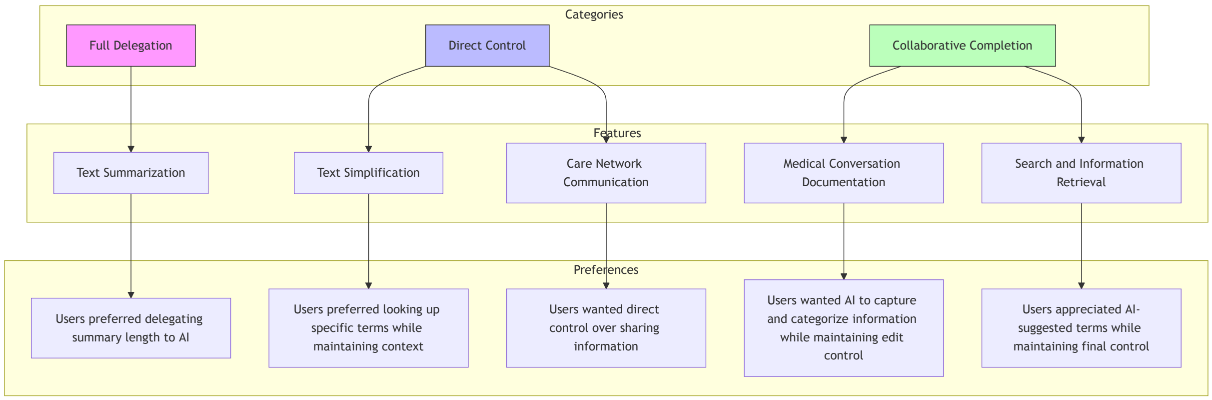

Figure 2: Framework for Older adults' Preferences in Automated Health Information Management Support Tools.

in search and information retrieval, participants appreciated AI-generated suggestions while maintaining control over final selections. This balanced approach was preferred for complex tasks that benefited from AI assistance but required user oversight. Figure 2 illustrates our framework for feature categorization based on the three preferred interaction approaches. While our framework reflects the preferences of older adults, it's important to consider whether these preferences are unique to this demographic or represent broader user needs across age groups. Prior work suggests that older adults' strong preference for direct control in tasks involving medical comprehension and information verification may be heightened compared to younger populations [31], who often exhibit greater comfort with automation. Future work should compare automation preferences across age groups to determine which aspects of our framework are specifically relevant to older adults versus which represent universal user needs in health information management.

6.2 Design Implications

Based on our findings, we also provide two key design implications for designing AI-assisted tools that support older adults' health information tasks at home, presented below:

6.2.1 Context-Aware Automation Implementation: Our findings suggest that implementing automation to support health information management should be carefully calibrated to the specific task context, aligning with Parasuraman et al.'s [35] broader framework for considering automation levels. We found that full automation can effectively reduce the cognitive burden for routine tasks with well-defined outcomes, such as text summarization and automated categorization of medical notes. However, for tasks involving medical comprehension or personal health decisions, such as understanding medical terms or sharing health information with caregivers, *designers should prioritize user control while providing AI assistance as needed.* Our study also revealed scenarios best suited for a mixed-initiative approach, including information search and retrieval (where AI suggests terms while users make final selections) and documentation of medical conversations (where AI captures information but users can edit and verify). These scenarios emphasize the importance of balancing automation with user control based on task characteristics and user requirements, particularly in healthcare settings.

6.2.2 Flexible Control and Progressive Information Access: Our findings emphasize the need for flexible control mechanisms and layered information access in health information management tools. Allen et al. [1] note that mixed-initiative interaction emphasizes the importance of flexible dialogue between user and system, where each contributes what they do best at the most appropriate time. This principle extends to both control mechanisms and information presentation. For instance, in medical conversation documentation, while AI handles initial capture and categorization, users should have straightforward mechanisms to review and modify the content, leveraging both system processing capabilities and human domain knowledge. Drawing from our participants' feedback and existing literature, we identified several key design principles. First, *the interface should support effortless switching between automated and manual modes, minimizing cognitive overload.* Findlater and McGrenere's work [13] on adaptive interfaces demonstrates that users perform better when they can easily adjust automation levels based on their needs. Second, following Shneiderman's principles of direct manipulation [39], *users should be able to easily undo or modify any automated actions.* Koch et al. [24] found that the ability to reverse automated decisions increases user trust and system adoption in healthcare settings, which was evident in our participants' desire to verify and edit AI-generated content. Additionally, *designers should implement progressive disclosure mechanisms where users can access more detailed information as needed.* This approach builds on research in healthcare interfaces [32] and cognitive load management for older adults [14], suggesting progressive measures may reduce cognitive burden. Our participants demonstrated these needs through their preferences for multi-layered access to medical conversations: beginning with AI-generated summaries for quick review, accessing categorized information (e.g., history, medication, exam) when needed, viewing complete transcripts for verification, and listening to original recordings for full context. This integrated approach to control and information access, as demonstrated in previous healthcare systems [34], supports both efficiency and thoroughness by balancing quick access with comprehensive understanding.

7 Conclusion

In this paper, we investigated older adults' preferences regarding automation levels in an AI-assisted tool for health information management. Through qualitative studies with nine older adults using our prototype, we found that preferences for automation varied significantly based on task characteristics. We developed a framework categorizing features into three approaches: full delegation, direct control, and collaborative completion. Our findings suggest that effective AI-assisted health information tools should implement context-aware automation calibrated to specific tasks and offer flexible control mechanisms with progressive information access.

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A PAPER PROTOTYPES

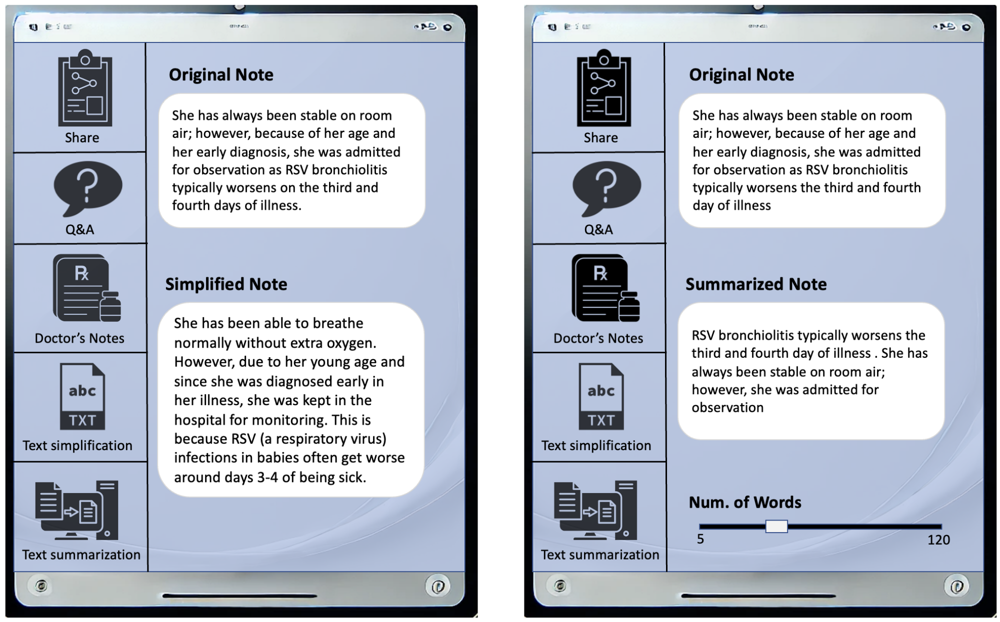

Figure 3: The text simplification and text summarization features are presented as the fourth and fifth options in the left menu, respectively. Users can control the length of the summary through a slider.

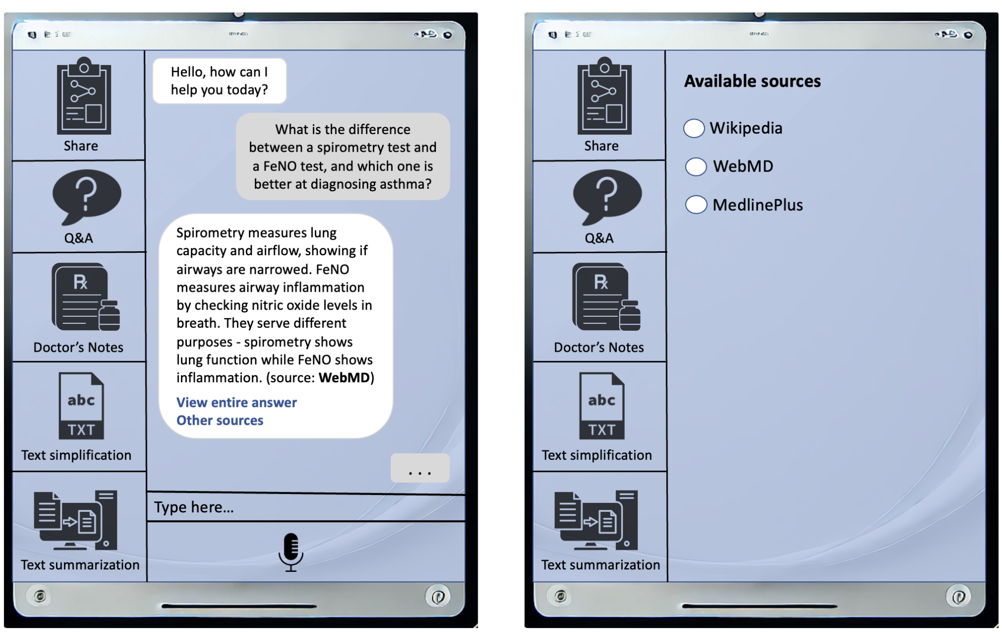

Figure 4: The Question & Answer feature provides answers to users' questions and displays the source of each response. Users can view both complete answers and references from multiple sources.

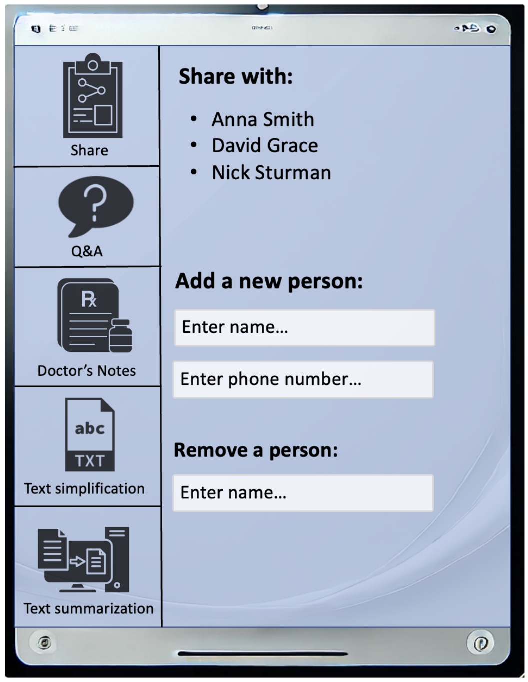

Figure 5: The Share feature enables users to share medical notes and other information with authorized stakeholders. Users can manage access by adding or removing individuals from their list.