Generative-AI Solutions for Connecting Seniors and Healthcare Providers

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***Abstract*—As the aging population grows, effective healthcare communication becomes increasingly critical, particularly for older adults managing multimorbidity (multiple chronic conditions). Traditional methods often fail to engage this demographic, leading to misunderstandings, inefficient care coordination, and increased provider workload. This paper presents a generative AI-driven solution integrating a multimodal chatbot and an AI-enhanced provider dashboard to bridge this gap. The chatbot employs a hybrid architecture combining intent-driven logic with large language model (LLM)-powered natural language understanding (NLU) for safe, context-aware interactions, while the dashboard synthesizes patient–chatbot dialogues, extracting key insights like sentiment trends, discussion topics, and tone analysis to aid clinical decision-making. Additionally, an LLM-assisted virtual meeting room enables real-time transcription, patient history summarization, interactive querying of past interactions, and streamlining consultations. By leveraging conversational AI, real-time analytics, and AI-assisted care coordination, this scalable solution enhances accessibility, promotes independent living, and improves provider efficiency, offering a transformative approach to patient-centered healthcare for aging populations.**

***Index Terms*—Older adults healthcare, Patient-provider communication, Large-language-model**

I. Introduction

The aging population and the increasing prevalence of multiple chronic conditions (MCC) are placing significant strain on healthcare systems worldwide. Older adults face complex health challenges that require continuous monitoring and personalized care. At the same time, healthcare professionals are burdened with heavy workloads, limiting their capacity to provide timely and effective patient support [1]. A critical issue in this landscape is communication between older adults and healthcare providers. Many patients feel disconnected, leading to misunderstandings about treatment plans and self-care [2]. Limited health literacy, difficulties in symptom reporting, and inefficient follow-up methods further exacerbate these challenges. Traditional approaches, such as manual phone calls or outdated digital platforms, often fail to effectively reach patients, increasing their sense of isolation and reducing the overall quality of care [3].

Home-based healthcare services have emerged as a promising solution to improve accessibility and alleviate provider workload [4]. Additionally, recent advancements in large language models (LLMs) present new opportunities to enhance patient-provider communication. Conversational agents (CAs) powered by LLMs can facilitate natural interactions, extract insights from conversations, and summarize key information [5]. However, deploying LLM-based CAs in healthcare settings poses several risks, including the generation of irrelevant or inaccurate responses [6]. These challenges are particularly pronounced for older adults, who may misinterpret AI-generated guidance, struggle with understanding nuanced information, or experience inconsistencies due to the limited memory of conversational models [7]. Further concerns regarding AI reliability, biased prioritization of health issues, and inaccurate severity assessments also remain unaddressed [8].

While existing research has explored various CAs—such as chatbots, embodied agents, and virtual assistants—for health information delivery and mental health support, many of these solutions suffer from usability limitations, cultural mismatches, a lack of explainability, and are often tailored to deal with a specific task, limiting their adaptability and broader applicability [9].

To address these gaps, this paper presents a generative AI-driven system designed to enhance communication in home-based healthcare. The main contributions of this research are as follows:

- *Multimodal Conversational Agent for Older Adults:* We introduce a chatbot that processes both text and voice, integrating intent-driven logic with LLM-powered natural language understanding (NLU). This hybrid approach ensures safe, context-aware interactions tailored to older adults' needs.
- *LLM-Augmented Clinical Dashboard:* Our dashboard synthesizes patient interactions, extracting sentiment trends, discussion topics, and tonal nuances. It also includes an LLM-powered assistant for real-time transcription, patient history summaries, and quick retrieval of past conversations, enhancing informed and efficient care. It streamlines decision-making, keeping providers informed without adding to their workload.
- *AI Safety and Reliability in Healthcare:* Our proposed system tries to balance LLM-generated responses with structured decision-support and human supervision, miti-

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gating hallucinations, inaccuracies, and misleading guidance. This ensures safer, more reliable AI-assisted healthcare interactions within a professionally monitored environment.

By addressing both technical and human-centric challenges, this research leverages the strengths of LLMs while mitigating their limitations. Our system enhances home-based healthcare by ensuring older adults' voices are heard and equipping providers with actionable insights, ultimately improving patient outcomes and reducing healthcare burdens. The paper is structured as follows: Section II reviews related work on telehealth, conversational agents, and LLM-powered healthcare interventions. Section III presents the proposed system architecture along with the prototype implementation of it, detailing its multimodal chatbot, LLM-powered provider dashboard, and AI-assisted virtual meeting room. Section IV addresses ethical and privacy concerns. Finally, Section V concludes the paper and outlines future directions for improving and refining the system through participatory and co-design approaches.

II. Related Work

A. Telehealth

The integration of digital technologies in healthcare has expanded significantly over the past decade, particularly as a response to challenges posed by pandemic-related restrictions [10]. Telehealth [11], the use of digital communication technologies, such as video calls, mobile apps, and remote monitoring, to provide healthcare services and consultations remotely, have improved access to remote care. However, these technologies often function in isolation, lack flexibility, and present challenges in integrating with conventional healthcare workflows. Many older adults struggle with such systems due to lower health and technological literacy, leading them to rely on more familiar communication methods, such as phone calls [12]. Furthermore, cognitive decline, sensory impairments, and unfamiliarity with medical terminology contribute to misunderstandings about their health conditions and treatment options, complicating their engagement with healthcare providers [13]. Research indicates that limited health literacy among older adults is associated with poorer health outcomes, including higher hospitalization rates and increased healthcare costs [14].

Healthcare professionals also face usability challenges with existing telehealth tools, often resorting to asynchronous messaging or phone follow-ups to compensate for system limitations. This workaround can result in miscommunications, incomplete symptom reporting, and additional administrative burdens. Standardized questionnaires, while intended to structure patient-provider communication, fail to offer the necessary customization for individual patient needs [15]. These shortcomings underscore the need for more intuitive and adaptable solutions to enhance communication, particularly for aging populations with chronic conditions requiring ongoing management [12].

B. Conversational Agents

One promising approach to addressing these communication barriers is the development of conversational agents (CAs), such as chatbots and voice-activated assistants (VAs). VAs, in particular, have gained traction due to their ease of use in retrieving health information and providing mental health support [16]. However, older adults often encounter difficulties using these tools due to design limitations, cultural differences, and a lack of personalization. The presence of multiple chronic conditions further complicates communication, as elderly patients with both mental and physical health concerns require tailored interaction strategies—an aspect that healthcare providers may not always recognize or address effectively [17]. Ineffective communication in such cases can lead to misunderstandings, non-adherence to treatment plans, and worsened health outcomes [18].

The rapid and staggering advancements in LLM development are unlocking new possibilities for enhancing CAs, enabling more natural and context-aware interactions. LLMs have demonstrated potential in various healthcare applications, including patient education, mental health assistance, and clinical risk assessment [19]. However, concerns remain regarding their reliability, with issues related to accuracy, bias, and inconsistencies in medical contexts. Rather than replacing clinical expertise, LLMs could serve as a bridge between patients and healthcare providers, facilitating clearer communication and ensuring critical information is effectively conveyed [20].

C. LLM-Powered Healthcare Interventions

Recent research on LLM-powered healthcare interventions highlights their potential to alleviate the workload of healthcare providers. However, many existing solutions rely on standardized frameworks that fail to address individual patient needs. A more effective approach would enable dynamic, interactive conversations with older adults, allowing for personalized health tracking, early issue detection, and improved self-reporting accuracy [9]. For clinicians, such a system could extract key insights from patient interactions, streamline follow-ups, and enhance decision-making without increasing their workload. Crucially, such an AI-driven system would act as an intermediary, ensuring continuity of care without providing direct medical advice [21].

Authors in [9] introduced Talk2Care, an LLM-powered system integrating voice assistants for patient interaction and an LLM-based dashboard for providers. While promising, it relied solely on LLMs, raising concerns about misinterpretations and the lack of long-term conversation history. Additionally, its provider dashboard remained relatively basic, limiting its practical clinical utility. Authors in [22] also explored LLM-powered voice assistants for older adults, focusing on medication adherence and after-visit summaries. Although it improved usability through co-design, it lacked deeper integration with clinical workflows and decision support.

To address these gaps, the proposed system in this paper enhances home-based healthcare communication through a multimodal conversational agent and an advanced LLM-augmented clinical dashboard. By integrating structured decision support and human oversight, it ensures personalized, context-aware interactions while mitigating AI reliability concerns. This approach balances automation with safety, providing a robust, scalable solution for AI-assisted healthcare.

III. System Architecture and Implementation

The proposed system integrates generative artificial intelligence (GenAI) with gerontechnology principles to address the unique needs of older adults and their care providers. As shown in Fig. 1, it comprises four core components: (1) a hybrid multimodal chatbot for older adults, (2) an AI-powered analytical dashboard for care providers, (3) an LLM-assisted virtual meeting room bridging communication between users and caregivers, and (4) a real-time data synchronization component using the Firestore database. The system is underpinned by a modular architecture that combines deterministic workflows with generative AI, ensuring reliability, safety, and adaptability in elder care contexts.

A. Hybrid Multimodal Chatbot for Older Adults

As illustrated in Fig. 1 the chatbot employs a hybrid architecture, integrating a deterministic intent-driven module with LLM-based NLU. A dedicated LLM agent handles intent detection, ensuring accurate interpretation of user input, while task-specific agents manage subtasks such as memory extraction, information highlighting, and audio insight extraction. These agents operate asynchronously, enabling parallel execution of multiple processes—such as audio insight extraction, memory retrieval, and response generation—which enhances the system's efficiency and responsiveness.

To ensure both adaptability and reliability, the chatbot follows a dual response generation strategy. For non-medical, open-ended conversations, it leverages a generative LLM (ChatGPT-4o[1]) to provide natural, empathetic responses. However, for medical-related inquiries or user-specific commands (e.g., adjusting speech speed), it employs Google's Dialogflow CX[2], which generates structured, deterministic responses. This method ensures compliance with safety and protocol requirements, which is critical in gerontechnology applications where the stakes can be high [23].

Optimally allocating between deterministic and generative AI flows is a crucial design decision, particularly given the chatbot's target audience of older adults. Deterministic flows are prioritized in situations where safety, reliability, and adherence to medical protocols are critical—such as when processing predefined symptom-related questions or handling specific medical instructions [23]. Meanwhile, generative LLM responses foster more natural and empathetic interactions, particularly in casual or emotionally supportive contexts [24].

This balanced approach enhances cognitive accessibility and user trust, aligning with established best practices in gerontechnology and human-computer interaction research. By seamlessly integrating structured and flexible AI-driven responses, the chatbot effectively supports both practical needs and emotional well-being, making it a powerful tool for older adult populations.

Fig. 2 provides the chatbot's interface, demonstrating its multimodal capabilities. The UI supports both text-based and voice interactions, ensuring accessibility for older adults. The chatbot's structured responses, as shown in the figure, reflect its dual response strategy—leveraging generative AI for open-ended dialogue while ensuring deterministic, rule-based responses for critical medical-related inquiries.

B. LLM-Powered Advanced Dashboard for Care Providers

The advanced dashboard aggregates patient conversations by summarizing key interactions, sentiment trends, and discussion topics, with summaries hyperlinked to original messages for traceability and context (Fig. 3). Beyond passive data presentation, it offers active management tools: care providers can add shared notes for internal communication, flag messages for prioritized attention, and create follow-up questions sent directly to older adults via the chatbot. Advanced visual analytics, such as spider charts mapping frequently discussed topics and heatmap calendars illustrating recurring health issues, further enrich the dashboard.

To ensure care providers remain informed, the system integrates a notification mechanism and a dedicated dashboard section for flagged interactions. Health-related inquiries asked by older adults which are beyond the chatbot's scope are automatically escalated to providers via real-time notifications, preventing urgent or medically relevant questions from being overlooked. Similarly, responses from older adults to provider-initiated follow-up questions are highlighted and surfaced as notifications, ensuring critical updates remain visible. This structured communication flow enables timely, actionable updates while maintaining an efficient workflow (Fig. 1).

Fig. 3 illustrates the dashboard's implementation as a web application. After logging in, care providers can select patients from the left panel and access key details—demographics, medications, and health concerns—at a glance. The right panel displays conversation summaries, highlighting key messages. Here, providers can access *Conversation Analysis* to review patients' chatbot interactions, add notes, and pose follow-up questions regarding any specific interactions (Fig. 4). The central section presents analytics, including spider charts and heatmap calendars, for deeper insights into discussion trends as well as a section enabling providers to add notes or initiate follow-up questions. Dedicated notification tools ensure urgent inquiries are promptly addressed without requiring providers to sift through lengthy conversation histories. The *initiate call* button at top allows providers to send call requests, which appear to patients upon chatbot interaction.

C. LLM-Assisted Virtual Meeting Room

The virtual meeting room facilitates direct and seamless communication between older adults and care providers, lever-

[1]https://openai.com/chatgpt/overview
[2]https://cloud.google.com/dialogflow/cx/docs

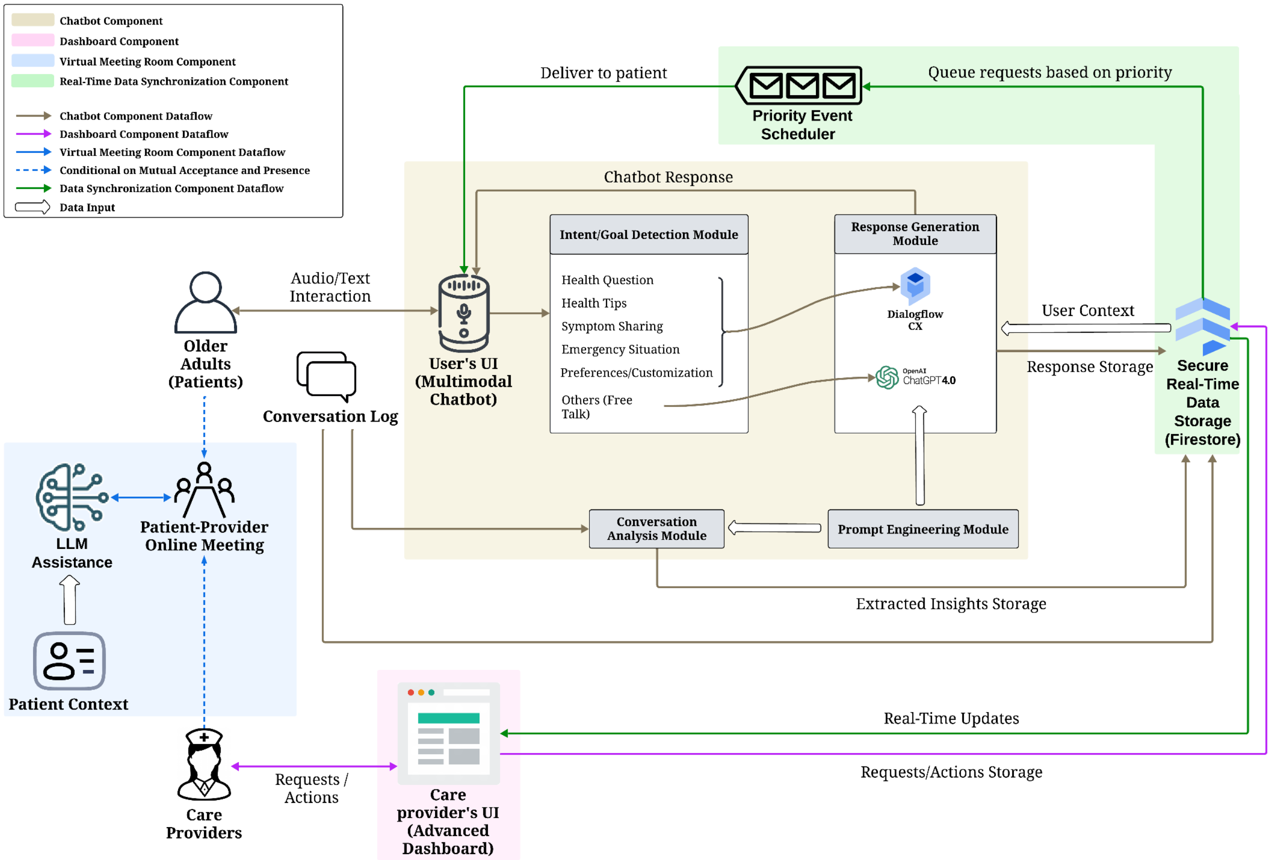

Fig. 1. System architecture showing interactions between older adults, care providers, and a generative AI system. It is divided into four core components, as discussed in Section III.

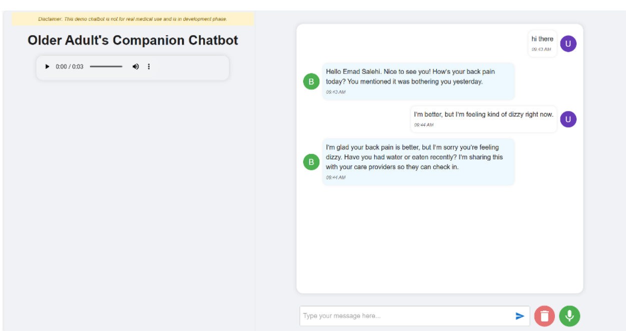

Fig. 2. Main interface of the hybrid multimodal chatbot web application, designed for older adults, supporting both text and voice interactions. The application is deployable on smartphones as well.

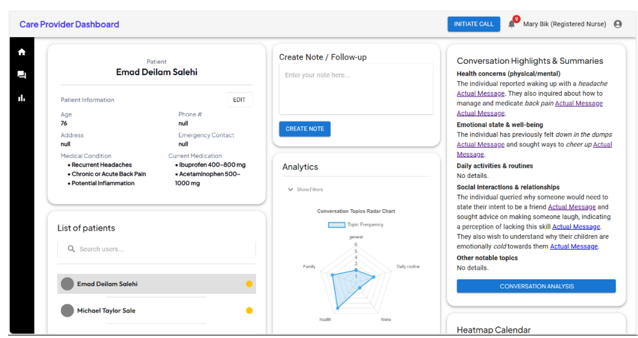

Fig. 3. Main interface of the advanced dashboard web application designed for care providers, offering patient insights, conversation summaries, and analytical tools for enhanced caregiving.

aging WebRTC[3] (Web Real-Time Communication) technology to ensure high-quality, low-latency audio and video interactions. This real-time open source communication protocol allows for secure, peer-to-peer connections, minimizing delays and ensuring a smooth consultation experience, even in environments with limited bandwidth. In this setting, the system harnesses real-time data and contextual insights to support more informed consultations. During a virtual meeting, an integrated LLM agent accesses comprehensive patient histories and extracts pertinent information, providing care providers with immediate, actionable insights. This assistance reduces

[3]https://webrtc.org/

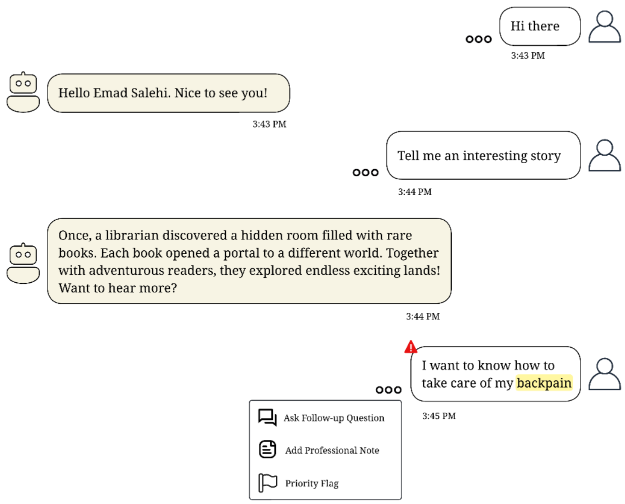

Fig. 4. Conversation Analysis page of the care provider dashboard, enabling message review, assigning notes for other care providers' review, or sending follow-up questions to older adults for better patient support.

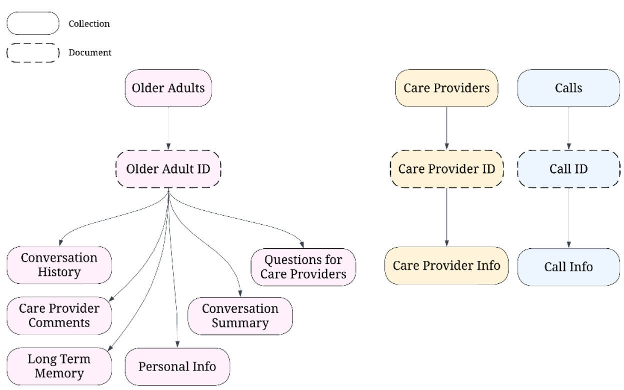

Fig. 5. Overview of Firestore's hierarchical structure, showcasing real-time cloud storage with a collection-document model. Some elements are collapsed for clarity.

the cognitive load on providers by ensuring that critical details are readily available, thereby streamlining the consultation process and enabling more focused and efficient patient care. By bridging the gap between asynchronous data collection and real-time interaction, the virtual meeting room plays a pivotal role in enhancing the overall quality and responsiveness of the care delivery system. The integration of WebRTC ensures that these consultations remain fluid, secure, and accessible, thereby improving communication efficiency between older adults and their care providers.

D. Real-Time Data Synchronization

At the system's core lies an event-driven architecture (EDA) [25], powered by a cloud-based synchronization layer that ensures real-time, bidirectional communication between the chatbot and dashboard. A centralized event broker (Firestore) facilitates low-latency interactions by instantly propagating user actions and provider interventions through lightweight listeners subscribed to database updates. This eliminates the need for manual refresh cycles or polling, ensuring seamless data synchronization across distributed components. As a result, care providers monitoring the dashboard receive immediate insights from chatbot interactions and provider interventions.

To optimize communication, the system employs a priority event scheduler that sequences provider actions before reaching older adults. Unlike instant updates sent to providers, this scheduler prioritizes events by urgency, ensuring critical interventions—such as emergency alerts—are delivered first, while lower-priority notifications like check-ins are queued accordingly. This structured flow prevents information overload, streamlines response management, and enhances user experience. By combining real-time data propagation with intelligent prioritization, the system ensures consistency, responsiveness, and timely decision-making in dynamic care environments.

Fig. 5 illustrates the implemented Firestore's structured document-based hierarchy, where each older adult user has multiple subcollections—such as *Conversation History*, *Conversation Summary*, and *Care Provider Comments*, among others. These subcollections enable asynchronous tracking of chatbot interactions, provider interventions, and summarized insights in real time. Similarly, each care provider has dedicated subcollections to store their information and recorded actions, ensuring seamless coordination across the system. Additionally, a *Calls* document maintains subcollections for active meeting rooms, storing relevant session details.

IV. Ethical and Privacy Concerns

LLM-powered healthcare communication systems improve remote patient-provider interactions but raise critical ethical and privacy concerns. The proposed architecture addresses these challenges with a structured, multi-layered design integrating deterministic logic, human oversight, and real-time synchronization to ensure safety, reliability, and trust.

A. Ethical Concerns

AI in healthcare must balance automation with human oversight to prevent misinformation and ensure clinical reliability. Since LLMs can sometimes generate plausible but inaccurate insights, our system combines LLM-based NLU with deterministic, intent-driven logic. Medical queries are processed through Dialogflow CX, using structured, context-aware questioning to gather relevant details before routing cases to healthcare professionals. This minimizes speculative AI recommendations and enhances patient safety. To ensure transparency, a summarization agent traces AI-generated insights back to their original sources, allowing clinicians to verify information before acting. This safeguards the integrity of medical guidance while maintaining trust in AI-augmented workflows. Another concern is the potential reduction of in-person care, particularly for older adults. While AI improves accessibility, it must not lead to delayed diagnoses or social isolation. To prevent this, our system integrates a WebRTC-powered, LLM-assisted virtual meeting room, ensuring real-time, human-centered patient-provider interactions. By embedding these safeguards, the system enhances care delivery while prioritizing patient welfare.

B. Privacy Concerns

Privacy is a key concern in LLM-powered healthcare systems, especially around collecting, storing, and sharing personal health information. To meet data protection regulations like HIPAA, the system adopts best practices from telehealth frameworks and uses a cloud-based synchronization layer for secure, real-time updates with minimal data exposure. Access is limited to authorized providers, and NLP techniques help anonymize or filter identifiable information when needed. The system also ensures transparency through a two-step informed consent process. Users are clearly informed about data use, storage, and sharing before engagement via consent forms, provider discussions, or automated notifications, accommodating different digital literacy levels. Ongoing reminders alert users when sensitive data is collected and suggest alternatives when appropriate. These measures build trust and help patients feel secure using the chatbot and dashboard.

V. Conclusions

This paper presents an AI-driven solution to improve healthcare communication for aging populations through a multimodal chatbot, an LLM-powered dashboard, and AI-assisted virtual meetings. A hybrid chatbot architecture ensures safe, personalized interactions by combining deterministic logic with generative AI. The provider-facing dashboard aggregates patient conversations for real-time insights, enhancing decision-making accuracy. The LLM-assisted meeting room streamlines direct communication, reducing consultation barriers. To balance automation with trust, the system integrates human oversight, data security, and transparency. Future development includes participatory design with older adults, care providers, and potentially a separate mobile app for family members to receive live updates, supporting independent aging. While the prototype has been implemented and described, a small-scale pilot with older adults and care providers is also planned for the near future to assess not only routing accuracy, perceived usefulness, and usability, but also user engagement, safety perception, workload reduction, and overall acceptability. Insights from this pilot will drive participatory co-design refinements.

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