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# How Multi-modal GenAI Helps Older Adults with Health Management? A Systematic Scoping Review

Ting Liu, Yiming Taclis Luo, Patrick Cheong-Iao Pang, Haopeng Zhang, Ao Xiang, Qin Yang

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# *Table of Contents*

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## *Abstract*

**Background:** The issue of population aging has emerged as a critical global challenge, with effective self-care and health management for older adults representing a pivotal solution to addressing geriatric health concerns. Against the backdrop of the widespread application of generative artificial intelligence (GenAI) in healthcare and management, it is imperative to investigate how Multi-modal GenAI can support older adults in maintaining health and managing well-being.

**Objective:** This study aims to systematically evaluate the role of GenAI in assisting older adults with health maintenance and management, comprehensively analyzing the application contexts, impacts, and developmental potential of diverse GAI tools across various health domains.

**Methods:** This study followed the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) guidelines. A comprehensive search was conducted across eleven databases (Web of Science, Scopus, PubMed, Medline, CINAHL, Cochrane, ACM Digital Library, IEEE Xplore, ScienceDirect, APA PsycInfo, and Google Scholar). A total of 26 articles were ultimately included in the study.

**Results:** GenAI tools effectively contribute to cognitive function maintenance, mental health support, and health condition management through personalized content generation and multimodal interaction. However, current applications are predominantly limited to cognitively normal, low-risk elderly populations, with insufficient coverage of high-risk groups and marginalized populations. Technical challenges persist, including over-reliance on text-based interaction, barriers in voice recognition, and suboptimal interface adaptability for elderly users. Ethical concerns such as data privacy risks and algorithmic bias remain under-addressed.

**Conclusions:** GenAI's promising role in enhancing older adults' health self-management through personalized and multimodal interventions, particularly in cognitive and mental health support. Strengthening interdisciplinary collaboration to integrate wearable technologies and edge computing, while establishing robust ethical frameworks for data privacy and fairness, will be critical to building a safe, equitable, and effective environment for active aging.

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# Original Manuscript

# How Multi-modal GenAI Helps Older Adults with Health Management? A Systematic Scoping Review

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## Abstract

**Background:** The issue of population aging has emerged as a critical global challenge, with effective self-care and health management for older adults representing a pivotal solution to addressing geriatric health concerns. Against the backdrop of the widespread application of generative artificial intelligence (GenAI) in healthcare and management, it is imperative to investigate how Multi-modal GenAI can support older adults in maintaining health and managing well-being. This study aims to systematically evaluate the role of GenAI in assisting older adults with health maintenance and management, comprehensively analyzing the application contexts, impacts, and developmental potential of diverse GAI tools across various health domains.

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**Conclusion:** GenAI's promising role in enhancing older adults' health self-management through personalized and multimodal interventions, particularly in cognitive and mental health support. Strengthening interdisciplinary collaboration to integrate wearable technologies and edge computing, while establishing robust ethical frameworks for data privacy and fairness, will be critical to building a safe, equitable, and effective environment for active aging.

**Keywords:** GenAI, Older adults, Health management, Systematic scoping review

## 1. Introduction

The accelerating global aging phenomenon has emerged as one of the most pressing challenges of the 21st century [1]. According to the United Nations' World Population Prospects 2022, the global population aged 65 and above surged from 131 million in 1950 to 727 million in 2020, with a projected increase to 1.5 billion by 2050 [2]. This unprecedented demographic shift has placed immense pressure on healthcare systems, particularly in chronic disease management, long-term care, and medical resource allocation[3]. The World Health Organization reports that elderly individuals account for over 50% of global healthcare expenditures, a proportion that continues to rise [4]. Traditional health management models, which rely heavily on healthcare institutions and professionals, are constrained by limited accessibility, high costs, and inefficiencies, rendering them inadequate to meet the growing needs of aging populations [5]. In this context, leveraging emerging technologies to enhance older adults' self-management capabilities has become a critical global priority [6].

Recent advancements in artificial intelligence (AI), particularly the emergence of GenAI, offer solutions to geriatric health challenges [7]. GenAI refers to AI systems capable of autonomously generating high-quality multimodal content (text, images, audio, video) from training data, with core technologies including large language models (LLMs) (e.g., GPT series) [8], diffusion models [9], and generative adversarial networks (GANs) [10]. Unlike traditional AI, GenAI not only analyzes information but also creates novel content, demonstrating vast potential in healthcare [11]. Current applications of GenAI in elderly health management exhibit diverse trends, with notable advancements in multiple domains. LLM-based conversational systems represent one of the most mature GenAI applications, capable of understanding complex medical scenarios and providing preliminary diagnostic suggestions and health management plans [12]. Advanced generation systems now integrate multimodal inputs for more natural interactions [13].

Diffusion model-based medical imaging technologies are transforming diagnostic approaches by generating high-quality CT/MRI images and enhancing image resolution through GANs [14]. Cutting-edge applications include converting 2D images into 3D visualizations or interactive VR scenarios for diagnosis, which simplify complex medical data into accessible visual reports for elderly patients [15]. Research also indicates that GenAI use in elderly care is often driven by hedonic motivation; entertaining content (e.g., storytelling, journaling, gaming, or virtual experiences) improves quality of life and mental health [16]. GenAI-powered virtual companions, equipped with emotional computing technology, recognize user emotions and provide psychological support [17]. Advanced digital humans with facial expression and voice emotion analysis enable empathetic interactions, alleviating loneliness among older adults and even supporting cognitive maintenance through daily engagement [18].

Furthermore, GenAI generates personalized health guidance tailored to individual health status, lifestyle, and cognitive abilities, presented through multimodal formats [19]. For instance, GenAI can create customized health manuals for diabetic patients, integrating dietary advice, exercise plans, and medication reminders based on glucose monitoring data [20]. Such multimodal health education is more accessible and comprehensible for elderly users compared to traditional text-based materials [21]. These diverse GenAI tools address aging-related health challenges across multiple dimensions. Globally, healthcare resource disparities and shortages are core challenges for aging societies [22]. GenAI alleviates pressure on medical systems by providing 24/7 basic consultations, enabling remote monitoring for high-risk elderly, and assisting primary care providers to improve diagnostic accuracy, thus bridging urban-rural gaps [23]. Traditional models struggle with issues like missed check-ups due to mobility limitations, complex medical information, and poor medication adherence [24]; GenAI resolves these through smart pillboxes with precise reminders, natural language explanations of medical instructions, and early risk detection via conversational analysis [25]. In response to rising mental health concerns, GenAI offers innovative solutions such as virtual companionship, cognitive training games, and emotion recognition-based psychological support [26]. Additionally, GenAI promotes healthy aging through personalized exercise planning, nutritional recommendations, and social activity matching [27].

Despite its potential, existing reviews on GenAI in older adults' health management predominantly focus on smartphone-based Chatbots with text-only interactions, neglecting multimodal GenAI technologies. Dunham et al. reviewed smartphone apps for chronic pain management in older adults [28]. while Zhang et al. summarized Chatbot applications in older adults' healthcare, noting their text-centric design and mobile deployment [29]. Chou et al. examined mobile health apps for mental health but emphasized Chatbot-driven psychological support [30]. These gaps hinder a comprehensive understanding of GenAI's current applications and trends in older adults' health. To address these limitations, this study investigates the following research questions:

(1) What are the geographic and temporal trends in GenAI tool usage for older adults' health management?
(2) Which GenAI tools are most widely applied in this field?
(3) In which specific health domains are GenAI tools utilized?
(4) What are the roles and impacts of GenAI tools in older adults' health management?
(5) What are the future potential and development trends of GenAI in this context?

This systematic scoping review adopts a rigorous PRISMA-ScR methodology to examine multimodal

GenAI technologies, not limited to traditional Chatbots. This research offers innovative solutions and scientific evidence for policy formulation, contributing to the advancement of healthy aging strategies. The findings will provide evidence-based insights for developers, policymakers, and healthcare professionals, promoting the rational application and sustainable development of GenAI in elderly health.

## 2. Methods

### *2.1 Search strategy*

This study screened relevant papers from eleven electronic databases: Web of Science, Scopus, PubMed, Medline, CINAHL, Cochrane, ACM Digital Library, IEEE Xplore, ScienceDirect, APA PsycInfo, and Google Scholar. The search date was July 28, 2025, and the search terms included "generative artificial intelligence", "GAI", "GenAI", "AIGC", "AI Chatbot", "ChatGPT", "GPT", "older adults", "elderly", "health", and "health management", etc. (see **Table 1**). The PRISMA-ScR checklist is provided in **Appendix A**.

**Table 1.** Selected databases and search formats.

| Database | Search formula |
|---|---|
| Web of Science | (("generative artificial intelligence" OR "GAI" OR "Gen AI" OR "AIGC" OR "AI Chatbot" OR "ChatGPT" OR "GPT" (All fields)) AND (("older" OR "older adults" OR "elderly" (All fields) )AND ("health" OR "health management" (All fields)) AND (Document Types: Article or Proceeding Paper) AND (Languages: English) |
| Scopus | (TITLE-ABS-KEY ("older adults" OR "elderly") AND ALL ("health" OR "health management") AND TITLE-ABS-KEY ("generative artificial intelligence" OR "GAI" OR "Gen AI" OR "AIGC" OR "AI Chatbot" OR "ChatGPT" OR "GPT")) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp")) AND (LIMIT-TO (LANGUAGE, "English")) |
| PubMed | (((generative artificial intelligence) OR (Gen AI) OR (GAI) OR (Gen AI) OR (AIGC) OR (AI Chatbot) OR (ChatGPT) OR (GPT)) AND (older adults)) AND (health) AND (health management) Filters: Full text |
| Medline | generative artificial intelligence AND Gen AI AND older adults AND health AND health management |
| CINAHL | ((MH "generative artificial intelligence") OR (MH "Gen AI") OR (MH "GAI") OR TI ("generative artificial intelligence*" OR "GAI*" OR "Gen AI*" OR "ChatGPT" OR "GPT")) AND ((MH "older adult*") OR TI ("older adult*" OR "elderly*") AND ((MH "health") OR TI ("health" OR "health management") |
| Cochrane | generative artificial intelligence AND Gen AI AND older adults AND elderly AND health AND health management |
| ACM Digital Library | [Full Text: generative artificial intelligence] AND [Full Text: gen ai] AND [Full Text: older adults] AND [Full Text: elderly] AND [Full Text: health] AND [Full Text: health management] |
| IEEE Xplore | ("Full Text & Metadata": generative artificial intelligence) AND ("Full Text & Metadata": Gen AI) AND ("Full Text & Metadata": older adult) AND ("Full Text & Metadata": health)<br>Filters Applied: Conferences Early Access Articles Journals |
| ScienceDirect | generative artificial intelligence AND Gen AI AND older adults AND elderly AND health AND health management "Article type: Research articles" |
| APA PsycInfo | generative artificial intelligence AND Gen AI AND older adults AND elderly AND health AND health management |
| Google Scholar | generative artificial intelligence AND GAI AND Gen AI AND AIGC AND ChatGPT AND GPT AND older adults AND elderly AND health AND health management |

### *2.2 Data Selection and Extraction*

All retrieved records were exported to EndNote software, and duplicate entries were removed. Two independent reviewers (TL and YL) conducted a preliminary screening of the article titles and abstracts based on predetermined inclusion criteria. Any discrepancies between the two reviewers were resolved through consultation with a third reviewer (PP). The inclusion criteria are as follows: (1) Studies specifically targeting individuals aged 55 and above; (2) Research on GenAI technologies for older adults in the field of health care and management; (3) Research on the application of GenAI technology; (4) Research articles; (5) Full-text articles and Conference papers published in English. The inclusion and exclusion criteria were designed with a specific focus on the application of GenAI. This study prioritizes empirical investigations of how GenAI tools are implemented in elderly health care and management, thereby excluding research that primarily explores elderly individuals' perceptions, attitudes, or opinions regarding GenAI in these domains. Additionally, review articles (e.g., narrative or systematic reviews) were excluded, as they synthesize existing literature rather than present original applications. To ensure comprehensive coverage of diverse research methodologies, the inclusion criteria encompassed qualitative, quantitative, and mixed-methods studies, thereby capturing a holistic range of evidence on the implementation of GenAI in practice. Interrater reliability revealed substantial to perfect agreement (κ= 0.795-0.815) between two independent reviewers for data selection, data extraction. These criteria are summarized in **Table 2**.

**Table 2.** Inclusion and exclusion criteria.

| Inclusion Criteria | Exclusion Criteria |
|---|---|
| A study only for people aged 55 and above | Studies involving people not aged 55 and above |
| Research on GenAI technologies for older adults in the field of health care and management | Research on GenAI technologies for older adults outside the field of health care and management |
| Research on the application of GenAI technology | Research on attitudes, views, intentions, benefits, obstacles, impacts, experiences, and usage demands towards GenAI technology |
| Research-type articles and Conference papers | Review articles, theses, non-academic publications, book chapters, etc. |
| Full text in English | Full text in other languages |

### *2.3 Data Charting*

Based on the review scope methodology guideline provided by the PRISMA-ScR [31] guidelines, the data extraction was developed. After trialing five articles, the table was further adjusted. It includes the following items: author, year, country, type of research methods, type of GenAI technology, type of input and output content, health application, target population, significance, impact, potential, and future trends. All data were extracted by two independent reviewers, and any disagreements during the data extraction process were resolved through consultation with a third reviewer.

For the reliability and validity of our synthesized evidence, we performed a critical appraisal of the methodological quality of every included study. This was accomplished using the Mixed Methods Appraisal Tool (MMAT) [32], a validated instrument specifically for assessing the quality of various study designs—quantitative, qualitative, and mixed-methods—in systematic and scoping reviews. The MMAT's evaluation is based on five criteria: the suitability of the research question and study design, the adequacy of data collection, the rigor of data analysis including the consideration of potential biases, and the validity of the final findings.

### *2.4 Collating, Summarizing, and Reporting the Results*

The research results were collected, summarized, and analyzed using descriptive statistics to describe the characteristics of the sample articles. Descriptive findings were presented through graphs and charts. The results were explained through narrative synthesis to address the research questions raised in the review, and this explanation was verified by all authors.

## 3. Results

A total of 1804 articles were retrieved through a systematic search, the search process and results as shown in **Figure 1**. Two reviewers independently screened the article titles and abstracts, excluding 1096 articles that were not directly related to the research topic, as well as 3 non-English articles. Then, the two reviewers conducted a thorough assessment of the remaining 61 articles. These studies were not the focus of this research, so 35 articles were excluded. The reason for exclusion was that the topic did not match the main focus of this study. Ultimately, 26 articles were determined to be included in this systematic review scope (see **Table 3**).

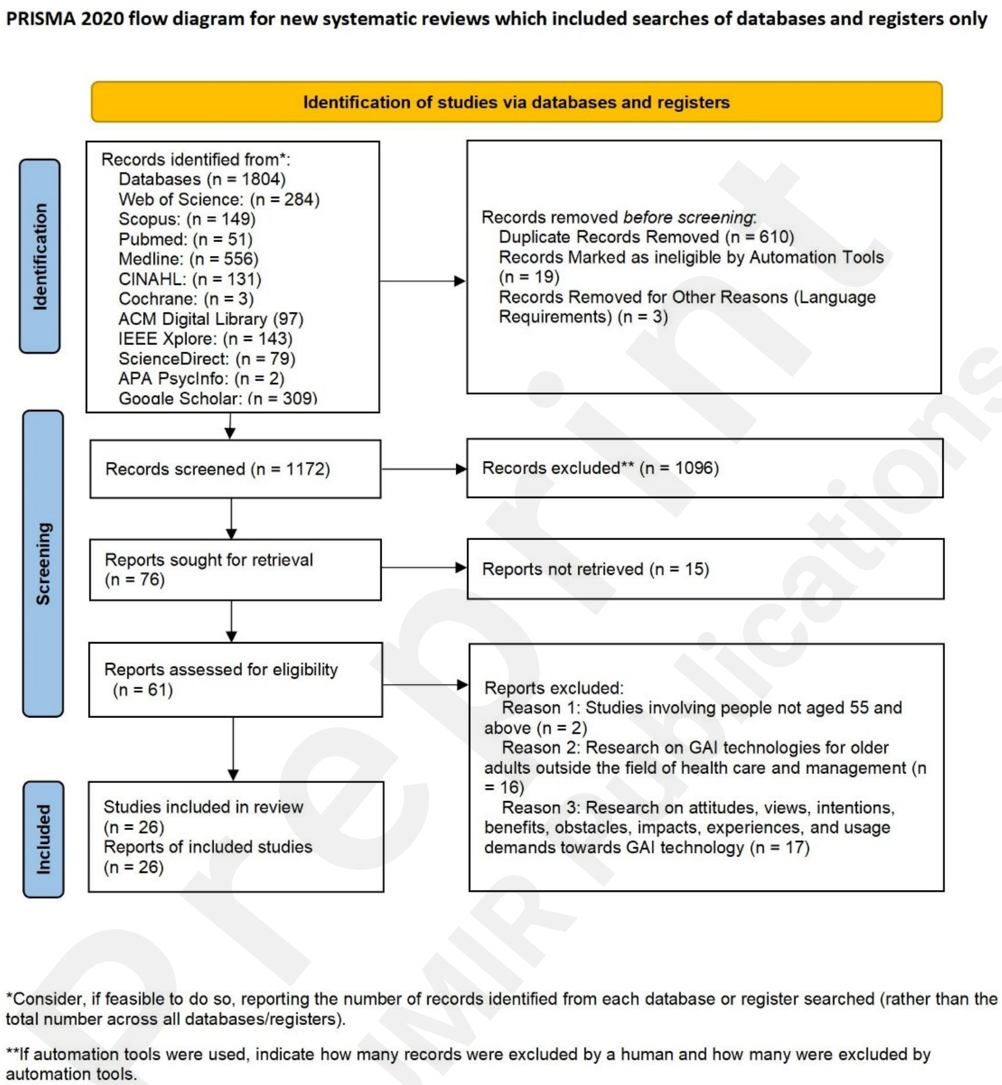


**Figure 1.** PRISMA flowchart.

**Table 3.** Overview of study characteristics.

| Author/ Year/ Country | Research Methods | GenAI Technology | Input and Output Content Type | Health Application | Target Population | Significance | Impact | Potential Trends |
|---|---|---|---|---|---|---|---|---|
| Satoh et al. 2024 Japan [33] | Mixed (Shapiro–Wilk test, Wilcoxon signed–rank test, comments of online meeting) | Music Trinity Generative Algorithm-Human Refined (MusicTGA-HR) | Text and music audio | Neurology-Frontal lobe functions and memory | 118 cognitively normal older adults | MusicTGA-HR intervention improves frontal lobe function and memory in older adults | Generating music through text can help older adults without professional music training to conduct non-pharmac[illegible] cognitive training, enhancing their cognitive abilities | The use of Ge[illegible] replace face-[illegible] pharmace[illegible] training ac[illegible] training, th[illegible] professionals will be needed to assist older adults |
| Pramod et al. 2024 India [34] | Quantitative (Partial least squares structural equation modelling) | GenAI system | N/A | Elderly health management | 314 older adults | GenAI [illegible] positi[illegible] support for the elderly | GenAI benefits elderly care via perceived ease of use | GenAI tools should have personalized [illegible] user interface, features, an[illegible] [illegible]tional functional design more suitable for the elderly |
| Xie et al. 2024 China [35] | Qualitative (Observation and in-depth interviews) | AI Chatbot | Text | Elderly health management-Exercise | 6 older adults | AI Chatbots help elderly [illegible] professional [illegible] information effectively | AI Chatbot [illegible] exercise [illegible] exercise perceptions | Improve the AI Chatbot b[illegible] leveraging more [illegible] language [illegible] mitigate [illegible] generating |
| Yu et al. 2024 | Quantitative（Pre-and [illegible] | Horticultural therapy- [illegible] | Artworks | Men[illegible] Elderly depression | 20 older [illegible] with depression | AIGC-horticultural [illegible] | AIGC–hor[illegible] | Explore [illegible] mechanism [illegible] long-term effects in depth [illegible] |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| China [36] | controlled study-independent t-tests） | combined with AIGC | | | | depressive symptoms and enhances mental health in older adults | intervention depressive symptoms | |
| Jin et al. 2024 China [37] | Qualitative (Thematic analysis) | GenAI music video | Text, image, video, and audio | Memory | 10 older adults | GenAI combined with music r improves memory in older adults | Language, tone, and emotions affect willingness to interact with GenAI; some perceive AI as lacking emotional warmth | GenAI re emotional e evoke emotional resonanc and it also demands higher-quality and more a image and content output |
| Yun et al. 2024 Korea [38] | Mixed（Controlled study-paired t-tests, and post-study interviews-thematically analyzed） | AI Chatbot | Text, and text-based games | Neurology-Dementia | 123 older adults | AI Chatbots based on AI demonstrate effectiveness in early dementia screening and personalized cognitive training | GenAI enhances cognitive and emotional well-being in older adults | AI Chatbot designs sh incorporate personaliz interactions. I nclude reinfo emotional res interactive e integrate social connectivity |
| Dragut et al. 2025 Spain [39] | Quantitative (Evaluation of tests) | AI Chatbot | Text, voice, and video | Language pathology-Speech disorders | 20 older adults | GenAI conversational agents based on LLM optimize language support and interaction for the elderly | GenAI dialogue agents correct language comprehension limitations | GAI agents are unable to handle user voices that exceed a certain soun threshold. The fu need to be trained on with dif disorders or specific speech features |
| Khan et al. | Quantitative | GenAI system | Physiological | Elderly | 30 older | [illegible] | GenAI systems [illegible] | Enhanced [illegible] timely, training m |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 2024 Pakistan [40] | (Eval tests) | for elderly-ti assisted living situations | parameters, the environmental information, and text | management | patients | enhance user-system interaction feedback mechanisms | per information satisfaction caregiver burden | adv techniqu in the infrastructure, cost-effectiv solutions and r standa learning algorithms, e AI frameworks, an centric design |
| McCARREN et al. 2025 Sweden [41] | Mixed (semi-structured interviews and questionnaire) | AI Chatbot | Text | Mental mindfulness | 15 older adults | LLMs crea pheral mindfulness coaches for older adults | Voice-responsiveness, a hol ou enhance the GenAI experience | Enhance interaction and ease of use personalized guidance |
| Tsai et al. 2021 Taiwan [42] | Quantitative (Cronbach's α value) | AI Chatbot | Text | Elderly management-Health knowledge learning | 14 older adults | AI Chatbots help the elderly health understand and access health information | Stable systems with minimal errors build user trust; users seek disease knowledge via Chatbots | The content i provided with pictur and videos. The texts can acc understandin prevention in a short t and the videos can cl explai information |
| Chou et al. 2024 Taiwan | Quantitative (The Fisher exact test, the Wilcoxon | AI Chatbot | Text, image, voice | Mental health-Stress | 35 older adults | AI Chatbots improve health accessibility, | Chatbots benefit in their depression/ | Et psychiatric personalized mental support can be provided b |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| [43] | signed rank test, analysis of covariance, and Spearman rank correlation) | | | | | awareness, and quality of life | loneliness | expand functionality of the Chatbot to effec depression among older adults |
| Bennion et al. 2020 United Kingdom [44] | Mixed (Qualitative description, and Mixed 2 × 3 analysis of variance, Post hoc 2-tailed t tests, independent t tests, and Simple linear regression) | AI Chatbot | Text | Mental health | 112 older adults | AI Chatbots alleviate loneliness and self-disclosure difficulties in the elderly | AI Chatbot has the potential for development in the field of electr psychological therapy for the elderly | Further evaluate health economic util of conversati context needs to b clinical outcomes b assessed over longer and system usability needs |
| Reed et al. 2025 USA [45] | Mixed (Interviews-thematic analysis, non-parametric test, a Wilcoxon Signed-Rank Test) | GAI images | Text and image | Memory | 34 older adults with at least one major mental illness, and English literacy (spoken) | P [illegible] image [illegible] health [illegible] l o n residents | GenAI-generated images from [illegible] emotions, fa [illegible] in long-term care | Need a more diverse sample and how it affects mood for [illegible] depressed at baseline. More randomized c trials are needed to evaluate the efficacy of mindfulness-based art therapies. whether GenAI images [illegible] reflection, disc empathy alone |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Bosco et al. 2024 USA [46] | Qualitative (Thematic analysis) | Voice Assistant, and AI Chatbot | Text and voice | Neurology-Alzheimer's Disease and Related Dementias | 15 older African American and Black adults | GenAI r[illegible] accessible content and technology to build trust and interaction preferences | Historical medical mistrust leads to reliance on traditional media (e.g., TV) and [illegible] information | Need to design a technology of credible accessible conte[illegible] users' repres[illegible] for health control, a time-efficient, and lever[illegible] community processes |
| Naseer et al. 2025 Saudi Arabia [47] | Quantitative (Evaluation tests) | Adaptive AI | Fall [illegible] alerts | Elderly care and management-Fall | 198 fall events | GAN and IoT sensors monitor health indicators, medication adherence, and environmental activities | The positive impact [illegible] discussed [illegible] enhancing care efficiency and the elderly people's rights and safety | New enhan[illegible] possible through devices powered AI including edge [illegible] for AI in-the-spot [illegible] without delays in cloud processing. And vi[illegible] scal[illegible] seamless between devices. |
| Kim et al. 2024 Korea [48] | Quantitative (Multiple regression analysis, Paired-sample t-test analysis) | AI Chatbot | Text, image, game | Memory | 32 older adults | Cha[illegible] therapeutic rela[illegible] meaningful connections with the elderly | Increased adherence to the AI Chatbot was correlated with reduced [illegible] participants, reflecting a deeper connection with the Chatbot | Explore the [illegible] variables [illegible] personalized [illegible] cognitive domains of [illegible] |
| Bosco et al. | Qualitative | Voice | Text and voice | Neurology- | 15 Black American | Poor GAI design may | Usability, accessibility, | Create cultural [illegible] inc[illegible] |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 2025 USA [49] | (Think Aloud-Thematic Analysis) | Assistant, and AI Chatbot | | Alzheimer's Disease and Related | older adults | increas[illegible] marginalized communities | relevance, and adoption are important for [illegible] Consent, privacy, and bias can impact the use of GAI for underrepresented community | [illegible] GAI [illegible] supported platform will follow |
| Olszewski et al. 2024 Poland [50] | Quantitative (Shapiro–Wilk test) | AI Chatbot | Text | Elderly management | 303 older adults and 270 young adult students | Most older adults prefer face-to-face interactions [illegible] Chatbots | Older adults prefer traditional media (e.g., TV) [illegible] pandemic-era tech advances | Greater involvement [illegible] adults in activities involving the use of [illegible] smartphones, computer software |
| Liang et al. 2025 Hong Kong [51] | Quantitative (Markov chain Monte Carlo, Chi-square, and independent sample t tests) | AI Chatbot | Text | Elderly management-Physical activity | 194 older adults | Chatb[illegible] health compliance with web-bas[illegible] interventions | With evolving knowle[illegible] graphs and machine learning, the Chatbot can ensure the accuracy of human-machine interactions, which fu[illegible] increases its efficacy | [illegible] Need a bigger data a[illegible] longer follow-up peri[illegible] the intervention |
| Miura et al. 2022 Japan [52] | Mixed (Interview questionnaire) | AI Chatbot | Text, voice, and image | Elderly management-Physical activity | 8 older adults and 19 younger adults | AI Chatbots facilitate self-[illegible] health conditions | The individuality of its effects still needs to [illegible] as a case study, [illegible] personal culture, habits, and life rhythms | Linking a Chatbo[illegible] wearables [illegible] deeply studied [illegible] achieve rea[illegible] including [illegible] trackin[illegible] person[illegible] questionnaires |
| Wang et al. 2021 USA [53] | Qualitative (Evaluation of tests) | AI Chatbot | Text | Elderly management | 1690 questions | AI Chatbots [illegible] real-time, pers[illegible] acce[illegible] | [illegible] interfaces wi[illegible] background requirements, but this may hinder [illegible] | Plan to [illegible] Chatbot voice assistant [illegible] realization, [illegible] technology [illegible] |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | information without technical barriers | adoption | |
| Thetbanthad et al. 2025 Thailand [54] | Quantitative (Evaluation tests) | Visual Question Answering model-based LLM | Text and image | Elderly medication management | 100 prescription labels | Zero-shot AI models clarify prescription labels for better medication management | Integrated ... tech ... personalized drug information for elderly patients/providers | The model effectively ... driven systems for drug label interpretation and medication management |
| Khamaj 2025 Saudi Arabia [55] | Quantitative (Focus groups and semi-structured interviews) | AI Chatbot | Text | Elderly management | N/A | AI-enhanced interfaces ... usability challenges in medical technology for the elderly | Chatbot functionality ... features ... enhance ... management and outcomes | More diverse participants could be recruited ... comprehensive insight ... availability and consistency of the Cha[tbot] ... different devices. ... with healthcare and industry experts. ... implement strong measures to protect personal health information. Through continuous development and testing. Encourage use ... professionals while ... the guidance ... provide[d] |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Imkome 2025 Thailand [56] | Quantitative (Means, frequencies, and standard deviations) | AI Chatbot | Text | Mental health | 44 older adults | AI Chatbots support mental improvement in older adults | Brief GenAI interactions yield meaningful benefits | Chatbot to ensure safe … reliable decisions Should … frameworks to en… responsible implem… of these technologies wh… assessing their effectiveness and ethicality. T… intra-subject variability, one should … measures for a more robus… establish… inter… Explo… methodologies, such as text, voice, and video, to intervent… individual… neces… feedback systems is cruc… for continuously enha… the user experience |
| Piau 2019 France | Quantitative (Mean values and standard | AI Chatbot | Text | Cancer | 9 older adults | AI Chatbot helps nurses enhan… | It helps optimize the follow-up of patients. Even for the elderly | Expand the sample size and follow-up period … long… |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| [57] | deviations) | | | | | monitoring, and improve patients' quality of life management, and the quality of life of elderly cancer patients | patient group with advanced age and limited technical literacy, they can also accept and use the health monitoring technology based on GenAI | Develop s methods for patie live alone or techn Further optimize the system functions. Adding auxi c a n c e r a randomized controlled trials to verify effectiveness. Cont evaluate the implementation process and usage of the technolog actual medical environment |
| Lin 2025 China [58] | Quantitative (Evaluation of tests) | EHMQA-GPT | Text | Elderly management | 26 question-answer pairs | LLM-based EHMQA-GPT improved knowledge related to elderly management through text data research | Investigate the cross-lingual scalability of instruction-tuning and evaluate integrating video instruction alignment strategies to assess the generalizability of GPT in multilingual, multicultural, and low-resource settings | GPT framework to broader ... expanding the ... diverse subf medicine |

### *1.1 Characteristics of Studies*

The final analysis incorporated 26 studies, with trends in publication and regional distribution characteristics of GenAI research in older adults' health examined (**Figures 2** and **3**). Temporally, the studies exhibit a clear exponential growth trajectory: from 2019 to 2022, the annual publication rate averaged only 1 article, which surged to 11 in 2024 and 10 in 2025, with the past two years accounting for 80% of the total publications. This indicates that GenAI applications are in a phase of rapid emergence. The low publication during the initial period (2019-2022) may be attributed to the limited maturity of GenAI technology and relatively scant attention to its potential in digital health solutions for older adults. In contrast, the recent surge is likely due to breakthroughs in GenAI technology, the intensifying global aging crisis, and strategic policy emphases on "digital health" and "smart elderly care" across nations. The convergence of GenAI's technical feasibility, the urgent demands of aging societies, and governmental policy drivers has collectively propelled research in this field.

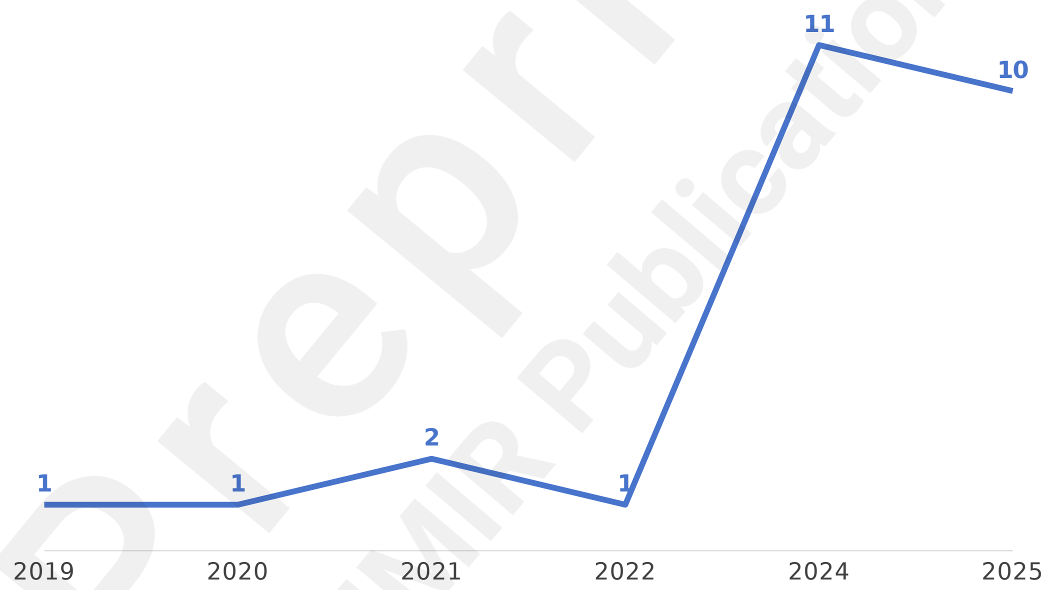


**Figure 2.** Annual number of publications.


**Figure 3.** Countries of publication.

Geographically, research output demonstrates significant regional concentration. The United States (4) and China (4), as the world's two largest economies and technological leaders, collectively contributed over a quarter of the total publications, establishing an unequivocal leading position. This distribution aligns with their "technology-economy-demographics" triad advantages. The United States leverages its foundational AI research capabilities, advanced medical technology innovation ecosystem, and extensive experience in addressing aging populations, granting it a first-mover edge in integrating GenAI technology with elderly health scenarios. China, with the world's largest elderly population, a rapidly evolving AI industry, and national policies promoting smart elderly care, has emerged as a significant research hub in this domain. Following these leaders are Japan (2), South Korea (2), Taiwan (2), Saudi Arabia (2), and Thailand (2).

While these countries/regions have smaller overall research capacities compared to the US and China, they exhibit distinct regional characteristics. Japan and South Korea, as the most rapidly aging societies globally, face intensified pressures on medical resources and caregiving due to deepening aging, prompting their research to focus on overcoming bottlenecks in traditional health management models through GenAI innovation. Taiwan and Thailand, with relatively robust digital infrastructure and growing elderly populations, are actively exploring localized applications of GenAI. Saudi Arabia, a Middle Eastern nation with substantial investment in technology, has aligned its research initiatives with national strategies for healthcare digital transformation, driving smart medical development plans. European welfare states such as Sweden (1), the United Kingdom (1), France (1), and Spain (1), though contributing fewer studies, have established niche expertise in GenAI ethics frameworks and human-AI collaborative care models, drawing on their long-standing standards in elderly health services and technological innovation. Developing countries, including India (1), Pakistan (1), and Poland (1), with limited but emerging research, reflect the global diffusion of GenAI applications in elderly health. Despite constraints in technological infrastructure or stages of population aging, these nations are beginning to explore how generative technologies can address gaps in traditional health services (e.g., improving healthcare accessibility for elderly populations in remote areas). Overall, the spatiotemporal distribution of GenAI research in elderly health is shaped by the interplay of multiple factors: technological maturity, aging pressures, economic and scientific capabilities, policy direction, and societal needs. The sharp increase in publications over the past two years corresponds to practical breakthroughs in GenAI and the escalating global aging crisis, while the leadership of the US and China stems from their synergistic advantages in cutting-edge R&D, vast elderly market demand, and strategic policy support. The differentiated distribution across other regions, such as high-aging countries prioritizing technology-driven solutions and emerging economies exploring cost-effective applications, highlights the diverse, context-specific demands for GenAI in addressing aging challenges worldwide.

Methodologically, the studies predominantly employed quantitative approaches, complemented by qualitative and mixed-methods designs (see **Table 4**). Quantitative research served as the primary evaluation framework for GenAI applications in older adults' health, leveraging structured data (e.g., pre-post differences, correlation metrics) to directly validate tool efficacy and underlying mechanisms. Specific statistical techniques included pre-post control designs (e.g., independent t-tests), analysis of covariance, Spearman's rank correlation, Fisher's exact test, and Wilcoxon signed-rank tests (n=12), with assessment-testing method (e.g., mean/standard deviation calculations, reliability/validity tests) appearing in three studies, reflecting a focus on standardized effect quantification.

**Table 4.** Research method types of studies.

| Research Method Type | Frequency (n) | Specific Methods |
|---|---|---|
| Quantitative | 12 | Evaluation of tests (n=3); Pre-and post-controlled study-independent t-tests; Cronbach's α value; Multiple regression analysis; Paired-sample t-test analysis; Shapiro–Wilk test; Markov chain Monte Carlo; Chi-square; Independent sample t tests; The Fisher exact test; The Wilcoxon signed rank test; Spearman rank correlation; Means, frequencies, and standard deviations; Mean values and standard deviations |
| Qualitative | 7 | Thematic analysis (n=3); Observation and in-depth interviews; Think Aloud-Thematic Analysis; Evaluation of tests |
| Mixed | 7 | Controlled study-paired t-tests and post-study interviews-thematically analyzed; Semi-structured interviews and questionnaire; 2×3 mixed ANOVA, Post hoc 2-tailed t tests, independent t tests, Simple linear regression; Interviews-thematic analysis; Non-parametric test; Wilcoxon Signed-Rank Test; Qualitative description; Mixed 2×3 analysis of variance; Post hoc 2-tailed t tests; independent t tests; Simple |

| | | |
|---|---|---|
| | | linear regression; Interview and questionnaire |

Qualitative studies (n=7) prioritized in-depth exploration of user subjective experiences, utilizing methodologies such as observational studies, in-depth interviews, thematic analysis, and think-aloud protocols combined with thematic coding. Through induction and thematic categorization of qualitative data, these approaches elucidated elderly users' perceived barriers, needs, preferences, and emotional responses to GenAI tools. Although representing a smaller proportion, qualitative methods were indispensable for understanding technology adaptability, such as interface usability and interaction naturalness, which quantitative metrics alone could not capture.

Mixed-methods research (n=7) functioned as a complementary paradigm, integrating quantitative statistical tests (e.g., paired t-tests, non-parametric tests) with qualitative techniques (e.g., thematic analysis, interview coding). Hybrid design models enabled cross-validation of data, such as joint analysis of questionnaire responses and interview feedback or correlating controlled experiment results with participants' subjective evaluations. This approach provided a more comprehensive understanding of GenAI tools' practical impacts across complex health scenarios.

### *1.2 Types of GenAI Technology*

Regarding technological type, general-purpose GenAI systems constitute the primary research focus. These systems, built on LLM or multimodal generation architectures, provide foundational functionalities such as health information interaction and chronic disease management support, serving as the core vehicle for technological intervention. Building upon this foundation, vertically integrated GenAI applications have further expanded technical boundaries. For instance, GenAI systems for assisted living leverage environmental sensing and demand prediction to enable medication reminders and emergency calls, facilitating home-based health monitoring. GenAI-generated music videos and images create personalized health education materials (e.g., animated disease explanations, medication procedure diagrams) through multimodal formats, enhancing the accessibility and engagement of health information. Additionally, horticultural therapy integrated with AIGC explores the fusion of generative content and therapeutic gardening, utilizing GenAI to produce customized gardening guidance videos or plant care prompts that support elderly psychological rehabilitation. These derivative applications are all underpinned by general GenAI technologies, with domain-specific adaptations (e.g., simplification of medical terminology, optimization for elderly cognitive load) enhancing their suitability for older adults.

In terms of functional implementation pathways, the core value of GenAI technologies lies in multimodal interaction support and personalized service generation. For multimodal interaction, some studies have integrated voice assistants with GenAI Chatbots, reducing operational barriers for elderly users through voice-based input/output while leveraging GenAI's natural language understanding to interpret complex health queries, thereby enabling more natural conversational flows. Regarding personalization, GenAI systems dynamically generate tailored content based on user history, such as dietary advice videos for diabetic patients, memory training game scripts derived from cognitive assessments, or companion dialogue strategies adjusted according to emotional analysis, significantly improving the precision of health management.

A small subset of studies has also explored the integration of GenAI with advanced cognitive technologies (e.g., emotion recognition, context-aware adaptation), though such applications remain limited in proportion. These efforts nonetheless signal future potential for deep personalization and situational awareness. Notably, current technological applications exhibit a significant homogenization tendency; over half of the studies concentrate on general-purpose GenAI Chatbots, whose core functions are limited to basic health consultations and simple task automation. In contrast, there is insufficient exploration of deeper needs such as complex health decision support, affective computing, and ethical risk control. This distribution may stem from the current maturity level of LLM, elderly users' preference for "humanized dialogue" interactions, and research resource allocation toward "low-risk applications." However, it also underscores the need for future research to broaden GenAI's functional boundaries in elderly health, particularly in validating cutting-edge directions such as multimodal content generation, adaptive learning, and human-AI collaboration, e.g., hybrid decision-making combining GenAI with professional expertise (see **Table 5**).

**Table 5.** Types of GenAI technology.

| GenAI Technology Type | Frequency (n) | Core Functions/Application Scenarios |
|---|---|---|
| General GenAI Systems | 11 | Basic health information interaction, chronic disease management support, and simple task automation serve as the foundational technology for other derivative applications |
| GenAI + Personalization | 3 | Dynamic generation of customized health solutions, adjustment of companionship strategies based on mood analysis, and improving service precision through user data adaptation |
| GenAI-Generated Multimedia (Music Video/Image) | 3 | Generation of personalized health education content, psychological rehabilitation support materials, enhancing information comprehensibility and engagement through multimodal formats |
| GenAI for Assisted Living | 2 | Elderly home-based health monitoring, environment perception, and demand prediction; age-friendly interaction design tailored for home settings |
| GenAI + Multimodal Interaction | 2 | GenAI Chatbots integrated with voice assistants, visually question-answering model-driven image-text interaction for health |

| | | |
|---|---|---|
| | | consultations, reducing operational barriers and optimizing natural interaction |
| Advanced GenAI Applications | 2 | Adaptive AI systems, exploratory applications for complex health decision support; currently low in proportion but indicating potential for deep technical integration |
| GenAI in Therapy Integration | 1 | Integration of generative content with horticultural therapy to assist in elderly psychological intervention and emotional management. |

### *1.3 Types of Input and Output Data*

The data interaction patterns of GenAI in elderly health applications demonstrate a multimodal input-output integration trend, characterized by a text-based foundation with progressive expansion into multimodal formats (see **Table 6**). Regarding input data types, text remains the most prevalent interaction medium, primarily conveying users' health inquiries (e.g., symptom descriptions, medication questions), needs (e.g., companionship requests, educational content preferences), and basic health data. Its dominance is closely tied to elderly users' familiarity with natural language communication and the low technical barrier of text input. Beyond pure text, some studies have begun integrating alternative input modalities, such as voice (e.g., verbal commands), images (e.g., electronic prescriptions, medical records), and physiological/environmental parameters (e.g., fall detection data, ambient temperature/humidity), to enhance the comprehensiveness and accuracy of health monitoring through multi-channel data collection. For example, combining voice and image inputs can more intuitively identify elderly users' operational intentions or manifestations of health issues, while physiological parameters directly support acute risk alerts (e.g., fall alarms).

For output data types, text continues to serve as the primary modality for GenAI feedback, delivering structured or unstructured information such as health advice, disease explanations, and emotional support. Its advantages lie in clear logic, ease of understanding, and alignment with elderly users' reading habits. Building on this, multimodal outputs have emerged as valuable supplements: music and audio are utilized for mood regulation or rehabilitation training assistance; images and videos visualize health information (e.g., medication procedure diagrams, disease education animations) to reduce comprehension barriers or provide dynamic companionship; gamified text interactions are explored for cognitive training, leveraging engaging tasks to boost participation; and a few studies have experimented with outputs like physiological parameter feedback charts or environmental adaptation suggestions. Notably, current multimodal output applications remain concentrated in specific scenarios, such as mental health support and chronic disease management, and the synergy between multimodal inputs and outputs is not yet widespread. This reflects both the technical complexity of integration and the prioritization of scenario-specific adaptation needs. Overall, the data interaction model of GenAI in elderly health is characterized by a text-centric core supplemented by multimodal elements. Text ensures reliable and universal basic interactions, while multimodal components (e.g., images, voice, and physiological data) address the diverse needs of elderly users, such as visual preferences, operational challenges, and emotional requirements, through targeted support. This layered design not only aligns with the current maturity of GenAI technologies but also embodies a user-centered, aging-adaptive interaction logic.

**Table 6.** Types of input and output data.

| Data Type (Input/Output) | Frequency (n) | Core Functions / Application Scenarios |
|---|---|---|
| Text | 13 | Basic health consultations, expressing needs, delivering health advice, explaining diseases, providing emotional support, as the most universally accessible interaction medium, adapted to elderly users' low technical barriers and reading habits |
| Text + Voice | 4 | Voice-based interactions, voice feedback, reduce operational difficulty through voice input, and enhance naturalness and accessibility via voice output |
| Text + Image | 5 | User-uploaded images for auxiliary diagnosis, generating visualized health information; image input improves the accuracy of health data collection, while image output lowers comprehension barriers for complex information |
| Text + Voice + Image | 3 | Multichannel interactions, dynamic feedback, combine textual logic, vocal naturalness, and visual intuitiveness to deliver comprehensive health support |
| Text + Music Audio | 2 | Emotional regulation, rehabilitation assistance, music audio output targets mental health needs and movement rehabilitation scenarios by providing sensory stimulation |
| Text + Video | 2 | Dynamic health education, virtual companionship content, and video output enhance the engagement and dissemination effectiveness of health knowledge through dynamic visual information |
| Physiological Parameters + Environmental Info + Text | 1 | Acute risk warning and environmental adaptation; input of physiological parameters and environmental data supports real-time health risk identification and context-aware interventions. |

| | | |
|---|---|---|
| Text + Game | 1 | Gamified cognitive training interactions improve elderly engagement and cognitive exercise effectiveness through game-like text tasks |
| Artworks | 1 | The generation of art therapy content serves as a supplementary tool for psychological interventions by stimulating emotional regulation through visual stimuli |
| Fall Data + Alerts | 1 | Fall monitoring and emergency response; dedicated to acute prevention scenarios with a single data type input, emphasizing real-time responsiveness |
| Text + Image + Voice | 1 | Comprehensive interactions; enhance accuracy in describing complex health issues through multimodal input synergy |
| Text + Image + Game | 1 | Integrated cognitive training and entertainment; multimodal intervention design targeting maintenance of elderly cognitive functions |

### *1.4 Types of Health Application*

The applications of GenAI in elderly health research primarily concentrate on four core domains: neurocognitive health, mental health, comprehensive health management, and specific disease interventions (see **Figure 4**). Among these, neurocognitive-related health issues dominate the landscape, encompassing subdomains such as Alzheimer's Disease and Related Dementias, frontal lobe functions and memory, and speech disorders. These applications leverage GenAI's multimodal interaction capabilities and personalized content generation to address age-associated cognitive decline through tailored interventions. For instance, conversational training modules enhance working memory capacity, image/video generation technologies assist in neurofunctional rehabilitation, and dynamic interaction strategies (e.g., simplified language instructions adapted to dementia patients' comprehension levels) are deployed based on cognitive assessment results. Beyond treatment, these interventions emphasize early prevention and functional maintenance, highlighting GenAI's potential to decelerate cognitive deterioration.

Mental health support represents another high-frequency application area, spanning contexts such as elderly depression, stress, mindfulness, and general mental well-being. GenAI demonstrates unique advantages in this domain through affective computing and adaptive interaction design. Chatbots simulate empathetic dialogue to provide immediate emotional companionship for isolated or depressed elderly (e.g., proactively adjusting topics to alleviate anxiety upon detecting negative emotions), while standardized psychological intervention protocols grounded in cognitive behavioral therapy principles are delivered via multimodal formats to facilitate self-regulation of emotional states. Notably, mental health applications are often integrated with cognitive training functions, forming a "cognitive-emotional" synergistic intervention model that amplifies comprehensive health benefits. Comprehensive health management, as a foundational application domain, covers the broadest range of scenarios (e.g., health knowledge acquisition, physical activity/exercise, fall prevention, and general elderly healthcare) but with relatively moderate depth.

These applications center on GenAI's information dissemination and behavioral reminder functions, such as answering health queries via natural language interaction, generating personalized exercise plans, or integrating environmental sensor data to provide fall risk alerts. While these interventions typically do not target specific diseases, they play an irreplaceable role in enhancing health literacy, maintaining basic physiological functions, and preventing common risks. A smaller subset of studies explores vertical applications for specific disease interventions, such as health management for cancer patients. However, such applications remain rare, likely due to the complexity of disease mechanisms, stringent data privacy requirements, and technical adaptation challenges. Overall, neurocognitive and mental health domains, as high-priority areas with significant elderly health risks and demands, attract the majority of technological investments. Comprehensive health management expands the beneficiary base through essential functional coverage, while specific disease interventions, though not yet scaled, offer promising directions for future precision medicine. This distribution reflects a strategic balance between addressing urgent clinical needs and promoting broad-based health maintenance, with emerging opportunities in targeted disease solutions.

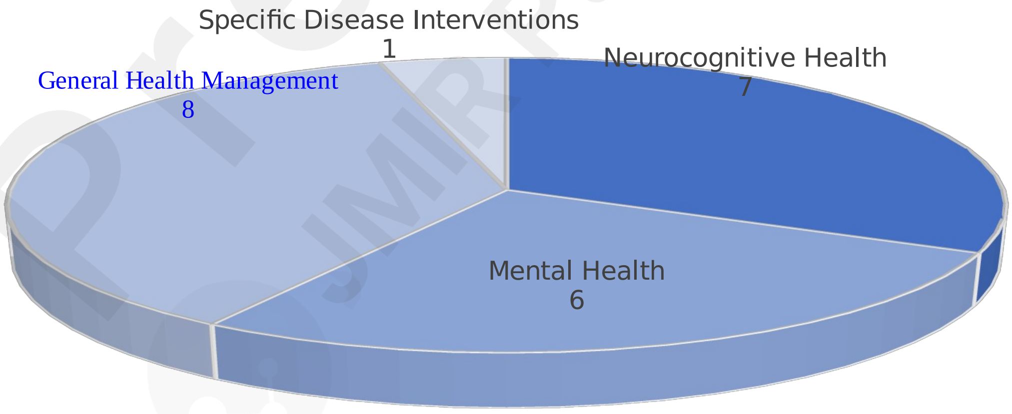


**Figure 4.** Types of health applications.

### *1.5 Target Population*

Older adults with normal cognitive function constitute the primary subjects of GenAI application research. These individuals are typically involved in evaluating the generalizability of GenAI's effectiveness in scenarios such as basic health information exchange, routine health management, and technology acceptance testing. Their relatively stable cognitive status enables clear articulation of needs and consistent participation in research protocols. Chronic disease populations and elderly patients form another critical research cohort. Studies focusing on this group center on GenAI's role in addressing complex health demands, such as chronic disease management, postoperative rehabilitation guidance, or acute condition prevention. The diversity of their health conditions and the intricacy of treatment regimens necessitate that GenAI systems possess enhanced capabilities for personalized content generation and multimodal data integration.

Mental health-focused populations represent key subjects in specialized demand scenarios. Research within this domain primarily assesses GenAI's efficacy in providing emotional support (e.g., alleviating depressive symptoms, intervening in loneliness), assisting cognitive behavioral therapy, and monitoring psychological states. The gradual inclusion of ethnic minority groups and populations with unique social attributes reflects growing attention to health equity. Such studies typically investigate GenAI's adaptability across culturally diverse contexts by targeting the distinct health needs of specific demographic groups. Although current sample sizes remain limited, these efforts provide crucial references for future scaled applications. Additionally, a small subset of studies targets special health status populations or utilizes indirect population data. For example, examining individuals with borderline cognitive impairment or those facing barriers to technology adoption. These investigations explore GenAI's potential in addressing nuanced or underserved health scenarios.

## 4. Discussion

### *1.6 Main Findings and Results of Studies*

This study, based on a systematic analysis of 25 articles, reveals the overall characteristics and core findings of research on the application of GenAI in the field of elderly health. From a temporal perspective, relevant studies have shown a significantly accelerated growth trend since their inception in 2019, with an explosive development in the past two years. This reflects the increasing attention from researchers, driven by the improved maturity of GenAI technology and the intensifying challenges of global population aging. Geographically, the distribution is concentrated, with technologically and economically advanced countries such as the United States and China playing a leading role. These countries, leveraging their advanced AI research foundations, large elderly populations, and proactive policies for smart elderly care, occupy important positions in the research. Meanwhile, countries with high aging rates, such as Japan and South Korea, as well as emerging markets like Saudi Arabia and Thailand, also demonstrate notable research activity.

The research methods are characterized by diversity, with quantitative research as the dominant approach, supplemented by qualitative and mixed-methods research. The types of technologies are focused on GenAI and its vertically derived tools. General GenAI systems form the core, gradually expanding to multimodal content generation and cross-domain integrated applications, and are complemented by interaction and cognitive enhancement technologies such as voice assistants and visual question-answering models. Text is the most common interaction medium, carrying health consultations and basic data transmission. Multimodal inputs, including voice, images, and physiological parameters, are gradually being applied to health monitoring, while multimodal outputs, such as music, audio, videos, and gamified texts, are used for personalized health services. The technological integration has continuously deepened from single-text to composite interactions.

The health applications cover neurocognitive health, mental health, comprehensive health management, and specific disease interventions. Among these, neurocognitive and mental health have become research focuses due to the high demand from the elderly population. The target populations mainly consist of ordinary older adults with normal cognitive functions, supplemented by those with chronic diseases and mental health problems. The gradual inclusion of ethnic minorities and special-status populations reflects concerns about health equity and the needs of marginalized groups. This not only demonstrates the great potential of GenAI in elderly health but also indicates that future research should further focus on in-depth technological adaptation, optimization of multimodal interactions, and inclusive design for a wider range of populations.

### *1.7 Significance and Role of GenAI for Older Adults' Health*

From the dimension of health functions, GenAI demonstrates particularly prominent effects in protecting and promoting elderly cognitive functions. Interventions such as MusicTGA-HR significantly improve frontal lobe function and memory performance in older adults, while GenAI-based image recall therapy tailored to individual life experiences maximizes mental health benefits [33]. Generative language model-driven Chatbots provide personalized cognitive training content, serving as efficient tools for early screening and intervention of neurodegenerative diseases like Alzheimer's [46, 49]. These applications not only validate GenAI's potential in maintaining cognitive reserve and delaying decline but also enhance intervention precision and acceptance through personalized adaptation.

In mental health support, GenAI via affective computing and natural interaction design serves as a critical tool for alleviating elderly loneliness and psychological stress [43, 44]. General-purpose AI Chatbots, through empathetic dialogue and real-time feedback, effectively reduce loneliness and promote self-disclosure [59]. Their "humanized" interaction features facilitate therapeutic relationships, offering emotional support for older adults in long-term care settings [60]. Complementary interventions, such as AIGC-generated content integrating horticultural therapy and music-based reminiscence therapy, further expand psychological intervention scenarios [36]. By engaging natural elements and nostalgic emotions, these approaches significantly alleviate depressive symptoms and elevate overall mental well-being [61]. These findings highlight GenAI's unique advantage in addressing the "emotional-cognitive" dual needs of elderly populations; it not only simulates the emotional warmth of human companionship through technological simulation but also delivers professional psychological support via content generation [62].

From the perspective of health information access and behavior promotion, GenAI substantially enhances the accessibility and efficiency of health management. LLM-based Chatbots transform complex health information into simple, intuitive text or voice content, enabling older adults to promptly grasp key information and precisely access needed resources [46, 49]. Their high accessibility and user satisfaction directly drive improvements in health behaviors. In chronic disease management, GenAI systems integrate IoT sensor data to enable real-time tracking of critical health indicators and environmental behavior analysis, providing data support for personalized interventions [40]. For elderly cancer patients, AI models interpret medication label information, while AI-enhanced Chatbot interfaces address usability barriers in medical technology adoption [54]. These solutions reduce the workload of healthcare professionals and improve treatment quality by enabling real-time symptom monitoring and minimizing recall bias [63]. Collectively, these applications establish a health management support system encompassing “information delivery-behavior guidance-technical assistance,” empowering older adults to participate more actively and scientifically in their health maintenance [64].

Furthermore, the social value of GenAI lies in advancing health equity and optimizing medical resource allocation [65]. By lowering technological barriers and offering multimodal interaction options, GenAI systems extend high-quality health services to traditionally underserved groups, such as older adults with low digital literacy or ethnic minorities [66], thereby reducing health disparities through their “inclusive” design. Simultaneously, AI Chatbots alleviate the workload of healthcare providers while enhancing service continuity and precision through real-time monitoring and targeted feedback, offering a technical pathway to optimize healthcare resource distribution [67].

### *1.8 Impact, Benefits, and Challenges of GenAI for Older Adults’ Health*

The application of GenAI in older adults’ health generates multidimensional impacts, encompassing significant enhancements in individual health functions and quality of life alongside challenges related to technological adaptability, interaction experience, and social acceptance [7].

GenAI demonstrates remarkable efficacy in maintaining cognitive function, supporting mental health, and promoting health management autonomy. In the cognitive domain, GenAI facilitates non-pharmacological cognitive training through personalized content generation. For instance, text-to-music interventions enable older adults without formal musical training to engage in memory and executive function improvement [33, 37]. GenAI-based image recall therapy, tailored to individual life experiences, activates long-term memory networks to enhance positive emotions and social interaction, effectively alleviating loneliness in long-term care facilities [45]. LLM-driven conversational agents reduce comprehension barriers via language correction, providing clear communication support for older adults with mild cognitive impairment while dynamically generating memory training tasks to delay Alzheimer’s-related cognitive decline [49]. In mental health, GenAI serves as a pivotal tool for psychological intervention through affective computing and adaptive interaction design. General-purpose AI Chatbots alleviate loneliness via empathetic dialogue and real-time feedback, offering sustained companionship for outpatients with stable depression and anxiety symptoms (e.g., during pandemic isolation) and significantly reducing psychological distress [43]. Mindfulness-based interactive content generated by GenAI assists elderly users in autonomous emotion regulation, while zero-shot learning models interpret medication labels with clarity and accuracy, mitigating treatment-related anxiety caused by information uncertainty [41]. Longitudinal interactions with GenAI further trigger deeper self-reflection, a "cognitive activation effect" positively correlated with reduced depressive symptoms, and some users establish trustful emotional bonds akin to interpersonal relationships through prolonged engagement [68].

Regarding health management autonomy, GenAI enhances self-efficacy by improving information accessibility and operational convenience [69]. AI systems leveraging user health profiles generate personalized recommendations in real time, with IoT sensor data enabling timely alerts for health status monitoring empowering older adults to manage their health independently [47]. Chatbots simplify complex medical information through plain-language explanations, boosting health awareness and reducing caregiver burdens, e.g., cancer patients' families efficiently manage symptoms and follow-up plans via AI-assisted tools, while healthcare providers allocate more time for personalized guidance due to automated reminders and data recording [57]. Moreover, GenAI's multimodal outputs (e.g., visualized health knowledge) bridge the "digital divide," enabling elderly users to autonomously navigate health management processes from monitoring to emergency response, thereby maintaining functional independence and dignity [54]. Despite these benefits, GenAI faces multifaceted challenges in real-world adoption among older adults, primarily in interaction adaptability, technological trust, and sociocultural suitability.

The predominant text-based input/output design of current AI Chatbots conflicts with age-related physiological declines. Visual impairments (e.g., difficulty reading small fonts), reduced hand dexterity (typing challenges), and diminished visual attention hinder efficient keyboard/touchscreen input [70]. Pure-text outputs (e.g., lengthy health guidelines or medication instructions) impose high cognitive loads, particularly for elderly users with low education or reading disorders who struggle to extract key information [71]. Additionally, suboptimal system responsiveness and unnatural voice synthesis (e.g., robotic tone, lack of emotional nuance) degrade interaction friendliness [72]. Research indicates elderly users prefer "warm, empathetic" technology, yet most Chatbots lack affective computing modules, failing to establish human-like emotional connections and often triggering perceptions of machine coldness [73].

Although GenAI offers convenient health information access, historical medical experiences lead some older adults to doubt the reliability of AI-generated content, favoring traditional media (e.g., TV health programs) or face-to-face consultations [50]. Digital access barriers, such as small fonts, complex workflows, and low-contrast interfaces in mobile apps/ Chatbots, further deter low-digital-literacy groups [74]. Privacy risks (e.g., health data misuse), algorithmic bias, and potential technical errors are common concerns prompting rejection of GenAI [75]. Establishing trust requires transparent data management, multilingual adaptation, and rigorous testing protocols. Technology acceptance is shaped by cultural background, lifestyle, and life rhythms [76]. Some elderly prioritize traditional services over digital options despite possessing device proficiency, believing "face-to-face interaction is more reliable [77]." Diverse needs across education levels, cognitive states, and sensory abilities remain unmet by most GenAI tools, lacking "tiered functionality adaptation [78]." These disparities underscore that GenAI's "universality" must be built on "precision personalization" through dynamic user preference learning [79].

Notwithstanding challenges, GenAI's long-term potential in elderly health is substantial. Advancements in voice interaction [39] (e.g., natural language understanding, emotional speech synthesis), multimodal fusion [37](e.g., integrated analysis of voice, images, and physiological parameters), and adaptive learning algorithms are expected to overcome current interaction bottlenecks, delivering more natural and supportive health services. Complementarily, robust policy and ethical frameworks are critical for GenAI implementation. Establishing age-friendly technical standards, transparent informed consent mechanisms for health data use, and targeted training resource allocation for underserved communities can reduce adoption barriers and promote health equity [80].

### *1.9 Potential and Future Trends of GenAI for Older Adults' Health*

The application potential of GenAI in older adults' health is significant, with future development trends centered on four key dimensions: technological deepening, interaction optimization, population adaptation, and ethical safeguards.

GenAI has demonstrated unique value in addressing elderly psychological issues, particularly in alleviating chronic loneliness, high shame, and sensitive conditions (e.g., depression, anxiety) [36, 43]. Electronic dialogues, such as AI Chatbots, reduce psychological resistance through non-face-to-face interactions, fostering higher levels of self-disclosure among older adults and emerging as a promising supplement to traditional psychotherapy. Future research must delve into mechanisms and long-term effects, such as expanding Chatbot functionalities to integrate mindfulness-based art therapies and personalized emotional feedback, enabling targeted management of emotional states across varying baseline depression levels [36]. Clinical utility should be evaluated through health economic analyses in real-world settings, with randomized controlled trials validating clinical efficacy. Additionally, enhancing GenAI's emotional expressiveness via natural voice modulation, empathetic language generation, and high-quality content output, while incorporating positive reinforcement, social connectivity, and other interactive elements, will improve intervention immersion and sustainability [81].

Current text-based GenAI tools will evolve toward multimodal interaction, combining voice (conversational dialogue), imagery (dynamic visualization), lighting (ambient atmosphere modulation), haptics (tactile feedback), and olfaction (sensory stimulation) to create immersive experiences (e.g., non-pharmacological mental health interventions integrating virtual journeys, scenario simulations, and artistic creation). These designs will prioritize the elderly physiological and psychological traits. such as large-font interfaces, voice-input alternatives to typing, and one-touch access to human assistance to reduce cognitive load [82]. Simultaneously, training on multilingual and region-specific cultural data will adapt GenAI to diverse linguistic expressions and health beliefs, achieving cross-cultural service accessibility [83].

Widespread GenAI adoption requires professional guidance, including training community workers and caregivers in basic digital literacy, GenAI functionality, and ethical risk identification [84]. Tiered tool systems (e.g., basic one-click operation for novices, advanced personalized settings for tech-savvy users) and community workshops will enhance digital literacy among low-technology-proficiency groups (e.g., the elderly with limited device experience). Research should incorporate diverse samples and conduct long-term follow-ups to assess GenAI's impact on health behavior changes (e.g., medication adherence, physical activity) [85].

Technological advancements will drive precise integration of GenAI functions, such as edge-AI-powered wearables enabling real-time health monitoring (e.g., heart rate, fall detection) and instant delivery of personalized health insights through localized data processing, reducing cloud dependency and enhancing privacy [47]. Ethical frameworks must prioritize data privacy protection (e.g., anonymization, access control), design user-controlled mechanisms (e.g., data authorization, content correction), and employ community-participatory development to align technology with elderly needs [86]. Cross-disciplinary ethics review boards (comprising medical, computational, and social science experts) will assess risks like algorithmic bias and emotional dependency, ensuring technological innovation upholds dignity and rights [87]. Collectively, these efforts will advance GenAI as a trusted, equitable, and effective tool for promoting healthy technologies, design, algorithms implications..

### *1.10 Limitations*

This study, based on a systematic analysis of 26 articles to focus on the application of GenAI in older adults' health. However, several limitations may affect the generalizability and external validity of the conclusions. First, the literature retrieval strategy may have resulted in insufficient sample representativeness among the included studies. The research populations predominantly consisted of older adults with normal cognitive function and low health risks, while studies targeting high-risk groups, such as those with cognitive impairments (e.g., mild cognitive impairment, early-stage dementia), multiple chronic disease comorbidities, or advanced age, were relatively scarce. Additionally, marginalized populations, e.g., ethnic minorities, low-income groups, and older adults with low digital literacy were underrepresented, leading to conclusions that may primarily reflect the needs and experiences of "technology-adaptive" subgroups rather than the full diversity of the global elderly population. Second, the exclusion of non-application-focused studies, e.g., reviews, non-academic publications, and research emphasizing attitudes, perceptions, or intentions toward GenAI rather than its practical implementation may have limited the comprehensiveness of the review. While this exclusion was intentional to maintain focus on the GenAI application, it potentially reduced insights into the broader contexts (e.g., user preference formation, social and cultural influencers) that shape GenAI adoption and effectiveness. These limitations underscore the need for cautious interpretation of the findings. Future research should prioritize expanding sample diversity to include high-risk and marginalized populations, enhancing long-term follow-up designs, optimizing real-world application testing, and deepening ethical and mechanistic explorations. Such efforts are essential to advance the safe, effective, and equitable application of GenAI in elderly health.

## 2. Conclusion

This systematic scoping review systematically searched 11 electronic databases and included 26 studies focusing on the application of Multi-modal GenAI in older adults' health. The aim was to summarize the intervention efficacy, current application status, and future potential of GenAI in promoting older adults' health. The findings reveal that GenAI demonstrates significant benefits in maintaining cognitive function, supporting mental health, and managing overall health. Its core strengths lie in multimodal interaction capabilities and personalized content generation. However, limitations persist in current applications: most studies focused on low-risk elderly populations, with insufficient coverage of high-risk groups and marginalized populations. Additionally, challenges remain in interaction design and unresolved ethical risks. Most studies were short-term interventions, with limited evidence on long-term efficacy and underlying mechanisms. Future research should prioritize expanding investigations into high-risk and marginalized populations to enhance inclusivity, optimizing multimodal interaction designs and age-friendly interfaces, and conducting long-term follow-ups to validate sustained effects. Furthermore, interdisciplinary collaboration is essential to integrate wearable devices, edge computing, and other emerging technologies, thereby constructing a secure, equitable, and scalable GenAI-supported ecosystem for elderly health. These efforts are critical to advancing healthy aging and ensuring the equitable benefits of GenAI across diverse elderly populations.

## Declarations

***Ethics approval and consent to participate***

Not applicable.

***Consent for publication***

Not applicable.

***Availability of data and materials***

The data used and/or analyzed during the current study are available from the corresponding author on reasonable request.

***Competing interests***

The authors declare no competing interests.

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***Authors' contributions***

T.L. and Y.L. proposed the idea to conceive and design this study. T.L. analyzed the data. T.L. completed the manuscript with the assistance of H.Z., X.A., and Y.Q. reviewed the data and revised the manuscript. P.P. supervised students and oversaw this work. All authors discussed the results and contributed to the final manuscript.

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# Supplementary Files