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Artificial Intelligence-Driven Smart Homecare: A Review of Applications, Challenges, and Prospects

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Abstract: With the accelerating global trend of population aging, traditional elderly care models are increasingly strained by limited service resources and growing quality demands. As a sustainable and cost-effective alternative, home-based elderly care has garnered widespread attention. However, older adults living at home often face critical challenges, including discontinuous health monitoring and insufficient emotional support. The rapid advancement of Artificial Intelligence (AI) technologies offers new pathways for developing intelligent elderly care solutions. This review systematically examines the major applications of AI in home-based care, focusing on two key domains: intelligent health monitoring and management and smart home environment systems. By analyzing representative research findings and practical implementations both domestically and internationally, this paper identifies core challenges across technical, user-centric, systemic, and ethical dimensions. Furthermore, it outlines future research directions, including personalized modeling, edge intelligence, empathetic human-AI interaction, multimodal data integration, and privacy-preserving strategies. This review aims to provide a theoretical foundation and a comprehensive framework to guide future research and practical advancements in AI-powered smart elderly care.

Keywords: Smart Homecare; Artificial Intelligence

Introduction

Population aging has emerged as a major global social challenge of the 21st century. In light of this demographic shift, providing sustainable, high-quality, and dignified eldercare services has become a pressing issue for governments and societies worldwide (Beard et al., 2016). Compared with institutional care, home-based eldercare presents inherent limitations in areas such as health management, safety assurance, emotional support, and emergency response, urgently calling for structural empowerment through new-generation information technologies(Qian et al., 2021).

As a core driver of current technological advancement, Artificial Intelligence (AI) has demonstrated transformative potential across various fields, including healthcare, smart homes, and intelligent manufacturing(Qian et al., 2021). In recent years, AI applications in smart eldercare have rapidly expanded, encompassing a wide range of capabilities — from monitoring vital signs and personalized health forecasting to voice-interactive companion robots, smart home automation, fall detection, and emergency response systems(Mohan et al., 2024). AI has thus become a critical technological pillar in the transformation and modernization of eldercare services.

Although a growing body of research has explored the potential of AI in the broader eldercare domain, comprehensive reviews focusing specifically on its applications, technical implementations, and development bottlenecks within the context of home-based eldercare remain limited. This review aims to bridge this gap by systematically examining the primary AI-driven application areas in home-based eldercare. We synthesize current research achievements, analyze key technical approaches and representative systems, and identify prevailing challenges and future trends from multiple dimensions, including technology, user experience, system integration, ethics, and policy. Ultimately, this paper seeks to provide a theoretical foundation and research roadmap for scholars and practitioners working at the intersection of AI and eldercare.

The main contributions of this review can be summarized as follows:

1. Scope specialization in home-based eldercare. Unlike prior reviews that broadly examine AI in healthcare or institutional settings, this paper specifically focuses on *home-based eldercare*, systematically covering two key domains: intelligent health monitoring and smart home environments.
2. Transparent and reproducible methodology. The review adopts a *structured narrative approach* supplemented with systematic literature scanning, with clearly defined databases, search strategies, timeframes, and inclusion/exclusion criteria, thereby enhancing methodological transparency and reproducibility.
3. Evidence mapping and technological synthesis. By organizing diverse AI approaches — including CNNs, LSTMs, GNNs, reinforcement learning, and Transformer-based models — across different data modalities and eldercare scenarios, this review provides a comparative synthesis of methodologies, applications, and performance challenges rather than a mere listing of technologies.
4. Multi-dimensional analysis of challenges. Beyond technical perspectives, this work critically discusses current bottlenecks from five interrelated dimensions: system robustness, user adaptability, standardization, ethical and privacy risks, and commercialization barriers, offering a holistic understanding of existing limitations.
5. Forward-looking research agenda. Based on current gaps and emerging trends, the review highlights future directions such as *personalized AI modeling, multimodal fusion, edge intelligence, and age-friendly human –AI interaction*, providing actionable insights for advancing both research and practice.

2. Methodology

To ensure transparency and reproducibility, this study adopted a structured narrative review approach supplemented with elements of systematic literature scanning. Searches were conducted across IEEE Xplore, PubMed, Scopus, using keyword combinations such as "Artificial Intelligence", "AI", "Machine Learning", "eldercare", "older adults", "aging population", "smart home", "assistive technology", "activity monitoring". The boolean search string is ("Artificial Intelligence" OR "AI" OR "Machine Learning") AND ("eldercare" OR "older adults" OR "aging population") AND ("smart home" OR "assistive technology" OR "activity monitoring"). The timeframe was restricted to publications between January 2020 and September 2025, thereby covering both foundational developments and the most recent advancements. Inclusion criteria were: (i) peer-reviewed journal articles or conference proceedings; (ii) studies focusing on AI-enabled technologies for home-based eldercare rather than institutional or hospital contexts; and (iii) articles published in English. Exclusion criteria were: (i) non-AI IoT systems such as purely mechanical or manual monitoring solutions; (ii) studies confined to pediatric or general healthcare settings without direct eldercare relevance; and (iii) grey literature including patents, marketing reports, or white papers. A total of 408 records were initially retrieved including 193 from IEEE Xplore, 158 from Scopus, and 57 from PubMed. After removing 74 duplicates, 334 articles remained for title and abstract screening. Following this process, 112 articles met all criteria and were included in the final synthesis. Reference chaining was further applied to capture seminal works not indexed in database searches. This structured process ensured that the review remains comprehensive and academically rigorous, while retaining the interpretive flexibility characteristic of narrative reviews.

2.1 Intelligent Health Monitoring and Management

Home-based eldercare faces persistent challenges in timely health risk detection, chronic disease management, and emergency response, as traditional approaches such as manual check-ins and periodic examinations lack continuity and sensitivity (Shi et al., 2025; Li et al., 2024). With the integration of Artificial Intelligence (AI), supported by the Internet of Things (IoT) and advanced sensing modalities, health monitoring is increasingly shifting toward personalized, precise, and real-time surveillance.

(1) Data acquisition and sensing modalities.

Wearables, ambient sensors, and vision-based systems form the backbone of data collection. Wearable devices—ranging from wristbands to intelligent textiles—enable continuous tracking of vital signs, while ambient sensors (infrared, pressure, accelerometer) capture activity routines and mobility pattern. Non-contact sensing, including radar and Wi-Fi-based approaches, offers privacy-preserving alternatives (Bačić et al., 2024; Qin, 2025). Compared to wearables, ambient and vision-based systems reduce compliance burdens but raise concerns over intrusiveness and data fidelity.

(2) Analytical approaches: strengths and limitations.

Health data analysis has evolved from rule-based systems to AI-driven modeling:

- **Conventional machine learning (e.g., SVM, decision trees):** Lightweight, interpretable, and suitable for limited datasets, but constrained in scalability and robustness.
- **CNN-based architectures:** Strong in feature extraction from vision data (e.g., fall detection), yet limited in capturing long-term dependencies (Katmah et al., 2023).
- **LSTM and RNN models:** Effective for physiological time-series forecasting (e.g., glucose, heart rate), though computationally demanding and often data-hungry.
- **Graph Neural Networks (GNNs):** Emerging tools to model interdependencies among multimodal signals, with potential for integrated health surveillance, though still lacking external validation in elder populations (Arora & Sinha, 2025).

Collectively, this comparison indicates that while deep learning approaches broaden the scope of detectable anomalies and trends, their deployment in real-world homecare remains hampered by computational cost and generalizability.

(3) Toward multimodal fusion and contextual awareness.

Recent efforts highlight the integration of heterogeneous data streams—combining physiological signals, behavioral patterns, and contextual cues — to enhance system accuracy. For instance, reinforcement learning and memory-augmented models have been applied to activity recognition in complex home environments (Jin et al., 2024; Lu et al., 2023). Vision-based anomaly detection techniques, such as temporal grounding and feature sampling, improve segmentation of daily routines but remain susceptible to privacy concerns and environmental variability (Yang et al., 2021; Tang et al., 2022). These findings suggest that multimodal fusion is essential for robust monitoring, yet interoperability and privacy remain critical barriers.

(4) Challenges and research agenda.

Several unresolved issues persist. First, generalizability across heterogeneous populations is limited, as most models are trained on small or homogeneous cohorts. Second, data sparsity and labeling bottlenecks hinder supervised approaches, motivating interest in few-shot, self-supervised, or federated learning paradigms. Third, user compliance remains fragile; older adults often resist wearables due to discomfort or memory lapses, leading to incomplete data streams. Finally, data governance and ethics—including secure transmission, storage, and consent management—require urgent attention (Wang et al., n.d.).

From these observations, three testable research questions emerge:

- *RQ1:* Can federated learning frameworks improve cross-household model robustness without sacrificing accuracy?

- *RQ2:* To what extent can edge intelligence reduce latency in anomaly detection below clinically actionable thresholds?
- *RQ3:* How can multimodal fusion be designed to balance accuracy with user privacy, especially in vision-based monitoring?

In sum, intelligent health monitoring has progressed from isolated sensing to AI-driven, multimodal analytics. However, achieving reliable, ethical, and widely adoptable systems will require not only algorithmic advances but also solutions for compliance, interoperability, and privacy—underscoring the importance of holistic, user-centered system design.

2.2 Smart Home Environment for Eldercare

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The home constitutes the central living space for older adults, directly influencing their safety, independence, and quality of life. Traditional residential environments, however, lack adaptive and responsive features to manage emergencies, detect behavioral anomalies, or ensure age-friendly accessibility. The application of Artificial Intelligence (AI) within smart home systems is transforming these spaces into dynamic environments that can sense, reason, and respond to the needs of elderly residents (Shi et al., 2025).

(1) Core sensing infrastructures and their roles.

Smart home environments typically rely on distributed sensor networks comprising motion, temperature, humidity, pressure, gas leakage, and smoke detectors. These systems provide continuous monitoring of activity and environmental changes, enabling both safety assurance and comfort enhancement. Compared to health-specific wearables, ambient sensor networks are less intrusive and reduce compliance challenges. However, their granularity is limited, and they struggle to differentiate between benign and hazardous inactivity.

(2) Intelligence in activity recognition and anomaly detection.

AI models significantly enhance the interpretive capacity of sensor data.

- **Probabilistic models (e.g., Hidden Markov Models):** effective in modeling sequential activities, yet sensitive to noise and limited in generalizing to new behaviors.
- **RNNs and deep learning architectures:** superior in detecting subtle deviations in activity patterns, such as prolonged immobility, but data-intensive and prone to overfitting (Farsi, 2021).
- **Transformer-based and hybrid attention models:** recently explored for robust human activity recognition in noisy home settings, offering improvements in adaptability (Y. Liu et al., 2025).

Despite progress, a recurrent issue is the lack of validation in complex, multi-occupant households, where overlapping activity signals pose challenges for reliable inference.

(3) Interaction modalities and usability.

Voice-based systems, powered by advances in speech recognition and natural language processing, provide intuitive control over lighting, appliances, and climate regulation (Chakraborty et al., 2023). However, recognition accuracy often declines for elderly users due to slow speech, slurred articulation, or dialectal variation (Li & Wang, 2024; Lu et al., 2024). Transformer and BERT-based models have demonstrated higher robustness (Gardazi et al., 2025), yet the challenge of balancing technical accuracy with user accessibility remains unresolved. Beyond voice, gesture recognition and multimodal interaction are being investigated but face high deployment costs and limited user familiarity.

(4) Decision-making paradigms: from rules to adaptive intelligence.

Early smart homes relied on rule-based systems, such as threshold-triggered alarms or static environmental controls. While transparent and predictable, these systems lack flexibility. AI-driven approaches, particularly reinforcement learning (RL), enable adaptive control that optimizes energy use and aligns with individual comfort preferences (Yang et al., 2021). However, RL-based systems demand large volumes of training data and risk unintended behaviors if not carefully constrained. The challenge is to ensure adaptive intelligence without compromising system stability or user trust.

(5) Barriers to real-world adoption.

Despite technical advances, three structural barriers hinder widespread implementation:

- **System robustness and reliability:** false alarms or malfunctions erode user trust, which is critical among older populations with low tolerance for technical errors.
- **Fragmentation and interoperability:** diverse commercial ecosystems lack standardized protocols, preventing seamless integration and data exchange.
- **Privacy and ethical concerns:** especially for camera-based monitoring, older adults may perceive surveillance as intrusive, creating resistance even when safety benefits are clear. Balancing functionality with dignity is therefore a pressing concern.

(6) Emerging directions: personalization and privacy-preserving intelligence.

The frontier lies in designing smart home systems that are both adaptive and respectful of user autonomy. Privacy-preserving sensing modalities (e.g., millimeter-wave radar, Wi-Fi CSI analysis) offer alternatives to intrusive cameras. Edge intelligence reduces reliance on cloud infrastructure, lowering latency and safeguarding personal data. Simultaneously, user-centered design approaches — integrating co-design with older adults — can improve acceptance and usability.

Research agenda.

The synthesis highlights several open questions:

- *RQ1:* How can smart home anomaly detection systems be generalized to multi-occupant households without inflating false alarms?
- *RQ2:* What design frameworks can ensure age-friendly voice and multimodal interfaces that accommodate linguistic and cognitive variability?
- *RQ3:* To what extent can reinforcement learning be safely deployed in critical smart home controls without compromising stability and user trust?
- *RQ4:* How can privacy-preserving sensing (radar, Wi-Fi) be validated against clinical-grade benchmarks while ensuring user acceptance?

AI-enabled smart home environments have evolved from rule-based automation to adaptive, learning systems that address safety, comfort, and independence. Yet large-scale deployment remains constrained by technical fragility, interoperability gaps, and ethical dilemmas. Future research must emphasize standardized protocols, rigorous validation in real-world households, and co-designed, privacy-conscious solutions. Only through such integrative approaches can smart homes mature into reliable, trusted infrastructures for aging in place.

3. Discussion: Current Challenges and Future Research Directions

As Artificial Intelligence (AI) technologies increasingly permeate the domain of home-based eldercare, their applications in health monitoring, emotional companionship, and smart home environments have demonstrated significant potential. At the same time, the role of information media—including online platforms, social media, and digital health portals — has begun to shape public perception, influence user behavior, and mediate access to eldercare solutions. However, both research efforts and real-world deployments reveal that AI-enabled eldercare still faces numerous unresolved challenges. These issues are not only technical in nature but also extend to user acceptance, system sustainability, ethical considerations, and policy support. To advance the deep integration and large-scale adoption of AI in eldercare services, it is essential to critically examine current limitations and outline future research and development priorities.

3.1 Current Challenges

(1) Limitations in Technical Performance and System Reliability

Although AI models have been applied to vital sign analysis, fall detection, emotion recognition, and speech interaction, the overall robustness and generalizability of these systems remain suboptimal. Elderly individuals exhibit high degrees of variability in physiological parameters, speech characteristics, and behavioral patterns, making it difficult for trained models to be directly transferred to practical scenarios. Moreover, health monitoring and behavior recognition rely on multi-source heterogeneous data, where issues such as signal noise, temporal misalignment, and data loss affect system accuracy and stability.

(2) Low Adaptability and Acceptance Among Older Users

Many current AI eldercare products lack proper adaptation to the needs and abilities of older users. User interfaces, interaction logic, and device designs often fail to align with age-friendly principles. Some older adults resist wearable devices due to discomfort or unfamiliarity, leading to low adherence and frequent data interruptions. Voice interaction systems often struggle with slow speech, unclear pronunciation, or regional dialects, resulting in decreased recognition accuracy and frustrating user experiences.

(3) System Fragmentation and Lack of Standardization

Smart eldercare systems are frequently developed by different companies or research teams, leading to non-standard hardware protocols and closed software interfaces. This fragmentation impedes interoperability between devices and results in data silos that limit cross-system integration. For instance, health monitoring data may not be effectively shared with home care or community health systems, hindering holistic health management. Such isolation also restricts the scalability and refinement of service models.

(4) Increasing Ethical Concerns and Privacy Risks

AI-enabled monitoring in private homes—especially involving video capture, voice recording, and physiological data analysis — raises significant privacy concerns. Many existing systems lack comprehensive privacy protection mechanisms throughout the data lifecycle, including acquisition, transmission, storage, and use. Inadequate user consent and unclear data ownership may result in privacy violations, data misuse, or psychological distress. Furthermore, the ethical boundaries of replacing human companionship with AI are still undefined, as overreliance on emotional robots could undermine natural social support networks.

(5) Slow Commercialization and Unfavorable Cost Structures

Advanced AI eldercare systems, particularly those involving multi-sensor fusion and high-performance computing, incur substantial development and maintenance costs. In the absence of economies of scale, these costs hinder adoption in individual households or care institutions. Additionally, the lack of standardized reimbursement policies, public subsidies, or service pricing frameworks slows market expansion and limits sustainable business development.

3.2 Future Research and Development Directions

(1) Developing Robust and Personalized AI Models

Given the individual variability among older adults, future research should focus on personalized modeling approaches. This includes the development of adaptive algorithms capable of continuous learning and model updates, improving system performance in diverse data environments. Additionally, enhancing model interpretability and visualization will help users and caregivers better understand decision-making processes, thereby increasing trust and adoption.

(2) Advancing Multimodal Data Fusion and Edge Intelligence

To improve decision-making accuracy, future systems must overcome the technical barriers of multimodal data fusion by integrating visual, speech, physiological, and behavioral inputs in real time. To reduce latency and enhance privacy, edge computing and lightweight AI models should be adopted to enable on-device processing of critical tasks—facilitating real-time, efficient, and privacy-aware solutions at the user end.

(3) Enhancing Human-AI Interaction with Emotional and Age-Friendly Design

AI interaction systems should account for the linguistic traits, emotional needs, and behavioral tendencies of elderly users. Developing dialogue systems with empathic capabilities and social memory functions can provide emotionally intelligent, human-like experiences. Simultaneously, user interface design and operational workflows should be optimized to minimize interaction barriers and improve accessibility.

4 Conclusion

The rapid advancement of Artificial Intelligence technologies has brought new vitality to traditional eldercare models, demonstrating particularly significant potential in home-based care scenarios. From dynamic health monitoring and emotional state recognition to smart home environmental control and rapid emergency response, AI is progressively shaping an integrated eldercare system that addresses physical well-being, emotional support, environmental adaptation, and safety risks. A systematic review of domestic and international literature reveals that AI applications in home-based eldercare are evolving from isolated functionalities toward integrated systems, with increasingly mature algorithmic models and platform architectures.

Nonetheless, several challenges remain for the widespread adoption and practical deployment of intelligent eldercare systems. These include insufficient adaptability of AI algorithms to individual differences among older adults, limited capacity for real-time multimodal data fusion, lack of standardized system interfaces, underdeveloped privacy protection mechanisms, and generally low technology acceptance among elderly users. Addressing these challenges will require interdisciplinary collaboration, policy-level support, and industry-wide standardization efforts.

Future research should focus on developing AI models with enhanced personalization and contextual awareness, promoting the adoption of edge intelligence in eldercare settings, and optimizing age-friendly human-computer interaction designs. Additionally, it is critical to establish comprehensive frameworks for data privacy and ethical governance, and to foster an open, collaborative ecosystem involving stakeholders from technology, healthcare, and social service domains. Through the deep integration of AI with eldercare services, it is possible to realize a truly human-centered model of proactive, continuous, and life-cycle-oriented home-based eldercare.

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