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Smart aging: integrating AI into elderly healthcare

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Abstract
Artificial Intelligence (AI) is transforming geriatric healthcare by improving early disease detection, optimizing patient management, and enhancing clinical decision-making. AI-driven tools, including machine learning (ML) algorithms, predictive analytics, and assistive robotics, are increasingly utilized to address challenges associated with aging, such as frailty, multimorbidity, polypharmacy, and fall prevention. These technologies can facilitate personalized medicine, improve diagnostic accuracy, and support healthcare administration by streamlining workflows and resource allocation. Despite its promising applications, the integration of AI in geriatric care presents several challenges, including issues related to data privacy, algorithmic bias, ethical considerations, and the digital literacy of older adults. Ensuring the inclusivity of AI models by incorporating diverse and representative datasets is essential to avoid disparities in healthcare delivery. Additionally, the role of AI must be carefully regulated to complement, rather than replace, human clinical expertise. This paper provides a comprehensive overview of AI applications in geriatric medicine, discussing its benefits, limitations, and future directions. By leveraging AI responsibly, healthcare systems can improve patient outcomes, reduce hospital readmissions, and promote aging in place. However, addressing existing challenges through interdisciplinary collaboration, policy development, and continued research is crucial to fully realizing AI's potential in elderly care.

Keywords Artificial intelligence, Older adults, Elderly care, Frailty, Cardiovascular diseases, Machine learning, Assistive robotics, Smart home

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Introduction

Longer life expectancy and declining birth rates are dramatically altering the global population landscape. By 2050, the proportion of people aged 60 and over is projected to double, increasing from 11 to 22% [1]. This transformation is reshaping the age structure of societies worldwide, challenging healthcare systems and redefining what it means to grow old in the twenty-first century [1].

As direct consequence, healthcare systems are increasingly confronted with the complex reality of older adults living with multiple chronic conditions [2]. It is estimated that around 95% of individuals aged 60 and over live with at least one chronic illness, and nearly 80% contend with two or more. Among the most prevalent issues are sensory impairments (hearing and vision loss), musculoskeletal disorders such as osteoarthritis and chronic back or neck pain, alongside chronic conditions like diabetes, COPD, depression, and dementia [2].

The implications of this population increase extend beyond increased healthcare expenditures; they also affect care models, resource allocation, and the burden on medical professionals, who must manage complex multimorbidity, polypharmacy, and age-related functional decline. The rising demand for long-term care, rehabilitation services, and personalized treatment strategies underscores the urgent need for innovative and scalable healthcare solutions capable of supporting healthy aging, improving clinical outcomes, and reducing hospital admissions [3].

In response to these challenges, technological advancements, particularly in artificial intelligence (AI) and digital health solutions, are emerging as critical tools to support geriatric care. AI-driven models can enhance early disease detection, optimize clinical decision-making, facilitate precision medicine approaches, and improve overall healthcare system efficiency, ultimately empowering elderly individuals to maintain their independence and quality of life for as long as possible [4].

This transformation necessitates a paradigm shift in healthcare policies, infrastructure, and professional training, ensuring that medical systems are not only reactive but proactively equipped to manage the evolving needs of an aging global population [5].

This narrative review explores the key applications of AI in geriatric healthcare, with a focus on its role in diagnostics, personalized treatment, disease prevention, care management, and its broader implications for healthcare delivery. As the global elderly population continues to grow, leveraging AI-based innovations will be crucial in developing sustainable, effective, and accessible healthcare models.

Methods

A comprehensive literature search was performed in PubMed, Scopus, and Web of Science for English-language articles published between January 2013 and March 2025. Search terms included combinations of:

> *"artificial intelligence", "machine learning", "deep learning", "digital health", "aging", "older adults", "geriatric care", "frailty", "multimorbidity", "polypharmacy", and "healthcare technologies".*

Additional sources were identified through manual screening of reference lists from relevant reviews and key articles. Inclusion criteria encompassed original studies, reviews, and position papers addressing the role of AI in clinical decision-making, early disease detection, care optimization, or functional monitoring in elderly populations. Exclusion criteria included articles focusing solely on pediatric or non-human populations, non-English publications, and editorials without original content.

Given the narrative nature of this review and following the SANRA (Scale for the Assessment of Narrative Review Articles) guidelines, no formal quality assessment of included studies was performed. Instead, selected studies were synthesized qualitatively, with emphasis on relevance, innovation and clinical applicability.

Diagnostic support in geriatrcs by AI technologies

As the elderly population is more susceptible to a range of complex and chronic conditions, early and accurate diagnosis becomes paramount. However, diagnosing elderly patients is challenging due to the presence of multiple coexisting conditions, frailty, and the commonality of age-related cognitive decline. AI technologies, particularly those involving machine learning (ML) and deep learning (DL), are emerging as powerful tools to assist clinicians in making faster, more accurate diagnoses [5, 6].

Machine learning (ML)

Machine learning (ML), a core component of artificial intelligence, enables systems to learn from data, identify patterns, and make predictions without being explicitly programmed for every task. In geriatric healthcare, ML holds significant promise for improving diagnostic accuracy, optimizing treatment plans, and enhancing predictive analytics, particularly in the context of chronic diseases and multimorbidity [6]. ML techniques are commonly classified into three primary categories: supervised learning, unsupervised learning, and reinforcement learning. By analyzing and interpreting large datasets, ML models can improve their performance over time as they are exposed to more data. Each ML model offers unique advantages and includes a range of algorithms that have been successfully applied in clinical research and practice [6].

Supervised learning in ML

Supervised learning is one of the most widely used approaches in ML, where an algorithm is trained on a dataset that has predefined labels. This means that for each input, there is a corresponding correct output that the model learns to associate. By analyzing these known relationships, the algorithm gradually improves its ability to make accurate predictions when faced with new, unseen data. In the field of geriatric healthcare, supervised learning can play a role in early diagnosis, risk prediction, and personalized treatment planning [7]. Several key algorithms are commonly used in AI:

- *Linear Regression:* This method is particularly useful for predicting continuous numerical values. For instance, it can be applied to estimate patient survival rates based on medical history, laboratory results, and comorbidities [8].
- *Logistic Regression*: Unlike linear regression, which predicts numerical values, logistic regression is designed for binary classification problems. In geriatrics, it can help determine whether an elderly patient is at high or low risk of falling, using factors like muscle strength, balance, and medication use [9].
- *Decision Trees & Random Forests*: These algorithms are well-suited for complex decision-making scenarios. In geriatric medicine, they can be used to analyze multiple patient characteristics, such as age, cognitive function, mobility status, and chronic conditions, to determine the best treatment strategy for conditions like heart failure, osteoporosis, or diabetes. Random forests, which are an extension of decision trees, provide more robust predictions by combining multiple decision trees into a single model [10].
- *Support Vector Machines (SVMs)*: SVMs are highly effective in image-based diagnostics, particularly for detecting neurological diseases like Alzheimer's disease. By analyzing MRI scans, these models can differentiate between healthy brain structures and those showing early signs of cognitive decline, aiding in early diagnosis and intervention [11].

Unsupervised learning in ML

Unlike supervised learning, where algorithms learn from labeled datasets with predefined outcomes, unsupervised learning operates without prior knowledge of categories or labels. Instead, it identifies hidden patterns and structures within the data, making it particularly useful for clustering, anomaly detection, and feature extraction in complex datasets [12].

In geriatric medicine, unsupervised learning is increasingly being applied to uncover subtle relationships between different health parameters, allowing for better disease management, risk stratification, and personalized treatment planning [12]. For instance, unsupervised learning is proving to be particularly valuable in analyzing Electronic Health Records (EHRs) to identify patterns of frailty progression in older adults. By examining years of patient data, ML models can detect previously unrecognized trends that contribute to frailty, such as gradual weight loss, decreased mobility, and fluctuating inflammatory markers. For instance, a study developed an Electronic Frailty Index (eFI) utilizing EHR data from hospitalized older adults. This index effectively identified frailty by analyzing various health parameters, facilitating early intervention strategies [12]. This allows clinicians to intervene earlier, implementing preventive measures that could slow down the progression of frailty and improve overall quality of life for elderly individuals.

Through its ability to reveal hidden patterns within complex health data, unsupervised learning is helping to refine predictive analytics, improve disease classification, and optimize treatment strategies in the rapidly evolving field of geriatric medicine. Some of the most commonly used unsupervised learning algorithms include:

- *K-Means Clustering*: This algorithm groups patients with similar characteristics into clusters. In geriatrics, it can be used to identify different subgroups of elderly patients based on their multimorbidity profiles. For instance, patients with similar combinations of cardiovascular disease, diabetes, and frailty may be grouped together, allowing clinicians to develop targeted interventions tailored to their specific health risks [13].
- *Principal Component Analysis (PCA)*: PCA is a dimensionality reduction technique that simplifies large datasets while preserving their most important features. This is particularly useful in genetic research for aging-related diseases, where datasets often contain thousands of variables. By reducing complexity, PCA enables researchers to identify key genetic markers associated with age-related conditions like Alzheimer's or osteoporosis [14, 15].
- *Autoencoders*: These are specialized neural networks designed for noise reduction and feature extraction. In wearable health monitoring, autoencoders can process continuous streams of data, such as heart rate, gait patterns, or sleep quality, and filter out irrelevant fluctuations, ensuring that only the most meaningful health insights are retained [16].

Reinforcement learning

Reinforcement learning (RL) is a unique branch of ML characterized by a trial-and-error approach, in which an intelligent agent learns to perform specific actions by interacting with its environment. The learning process involves receiving feedback in the form of rewards or penalties, which guides the agent toward the most effective strategies. For instance, a study demonstrated that rewards led to slower learning but promoted generalization, whereas punishments led to faster learning but impaired generalization, highlighting the distinct roles of positive and negative feedback in RL processes [17].

This methodology has seen extensive use in fields such as robotics and automated decision-support systems [18]. Within geriatric healthcare, RL is becoming increasingly valuable in personalizing patient care and enhancing autonomy. RL algorithms have demonstrated significant potential in personalizing medication regimens by continuously monitoring real-time patient responses to ensure optimal dosing schedules tailored to individual needs. For instance, a study applied RL to optimize insulin dosing for individuals with type 1 diabetes, adjusting for factors like high-fat meals and postprandial aerobic exercises. The RL-based system improved postprandial glucose control and reduced hypoglycemic events, showcasing its efficacy in personalized treatment [19].

Similarly, another study employed deep RL to optimize warfarin dosing, a medication with a narrow therapeutic range. The RL model outperformed traditional dosing protocols by better maintaining patients within the desired therapeutic range, thereby minimizing risks associated with incorrect dosing [20].

Moreover, RL significantly contributes to the functionality of robotic assistants designed for elderly care. These AI-powered robots can help older adults maintain independence, support mobility, and assist with daily activities, adapting their behavior according to user interactions and preferences [21]. In conclusion, the application of ML in geriatric healthcare presents significant potential to improve diagnostic accuracy, personalize treatments, and enhance overall quality of life among elderly individuals. By leveraging advanced algorithms, clinicians can effectively manage the complexities associated with aging populations, facilitating proactive and personalized care strategies. Figure 1 summarizes the main MI techniques.

Data processing in machine learning

Effective use of ML in geriatric healthcare relies heavily on carefully processing, structuring, and validating the data. This process involves several stages, each essential for creating robust and accurate predictive models.

Data collection

The initial stage in ML involves gathering comprehensive and high-quality data from various relevant sources. In geriatric healthcare, these typically include EHRs containing extensive historical medical information, wearable device data (such as heart rate monitors, activity trackers, and fall detection sensors), medical imaging like CT scans, MRIs, and PET scans, as well as patient-reported health outcomes, which provide insights into

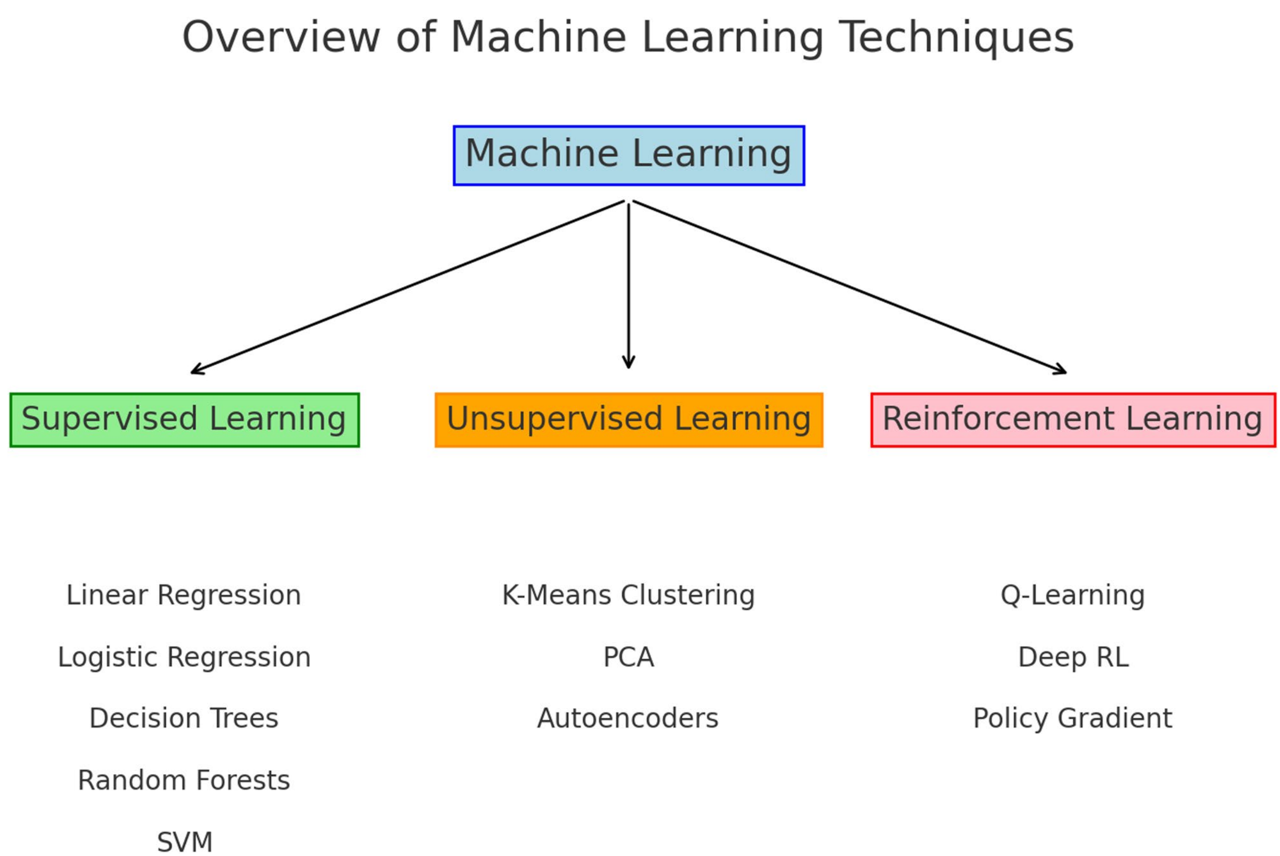

Fig. 1 Overview of Machine Learning Techniques. Machine Learning (ML) techniques are commonly divided into three primary categories: supervised learning, unsupervised learning, and reinforcement learning. Each category encompasses a range of algorithms widely applied in healthcare research, including linear and logistic regression, decision trees, random forests, support vector machines (SVM), k-means clustering, principal component analysis (PCA), autoencoders, Q-learning, deep reinforcement learning (Deep RL), and policy gradient methods

patients' perceptions of their health status, symptoms, and quality of life [22].

Feature engineering

Once collected, data needs to be structured appropriately, which involves a process known as feature engineering. During this step, ML algorithms identify, select, and optimize key variables or "features" from the raw data to improve predictive accuracy [23]. For instance, when building models to predict frailty syndrome in older adults, ML algorithms might particularly focus on features like gait speed, grip strength, and trends in weight loss, as these factors have strong predictive relevance for frailty progression [24, 25].

Model training and validation

Following feature engineering, ML models are trained using historical data sets. The models "learn" from patterns and relationships within these datasets, becoming capable of making accurate predictions [26]. To ensure that the trained model generalizes effectively to new, unseen data, it must undergo validation. This typically involves techniques such as cross-validation, where the model is repeatedly tested across different subsets of data to avoid overfitting, meaning the model performs well not only on historical data but also on new patient data [26].

For instance, ML models designed to predict fall risk in older adults are typically developed by training on historical fall incident data and subsequently validated using new patient records to assess their accuracy and practical utility. A study developed and validated an ML-based prediction model for serious fall-related injuries among community-dwelling older adults. The model was trained on data from 2018 and validated on data from 2019, achieving an area under the receiver operating characteristic curve of 0.700, with sensitivity and specificity rates around 65% [27].

Similarly, another study focused on developing and externally validating an ML-based fall prediction model for ambulatory nursing home residents. The model aimed to predict fall occurrences within six months after baseline assessment, providing staff with an effective and user-friendly fall-risk assessment tool [28].

Examples of AI applications in geriatric healthcare

AI is increasingly being explored in geriatric healthcare to assist in diagnostics, treatment optimization, and patient monitoring. Its applications range from fall risk assessment and cognitive decline detection to medication management and rehabilitation support. AI-driven technologies also contribute to remote monitoring and clinical decision-making, aiming to enhance elderly care and reduce hospitalizations. Figure 2 provides an overview of key AI applications in geriatric healthcare, illustrating its role in various aspects of patient management.

Cognitive and neurodegenerative disorders

Dementia, including Alzheimer's disease (AD), is one of the most prevalent and challenging conditions affecting older adults. AI is increasingly being used to detect early signs of dementia through the comprehensive analysis of multiple biomarkers.

Neuroimaging analysis DL models have been trained extensively on neuroimaging data to identify subtle structural changes in the brain associated with dementia. Beheshti et al. developed a computer-aided diagnosis system using structural MRI data. Their approach involved extracting voxel-based features from regions with significant gray matter atrophy and employing a support vector machine for classification. The system achieved high accuracy in differentiating mild AD patients from healthy controls and in classifying progressive MCI versus stable MCI, indicating a high potential for early diagnosis [29]. Furthermore, AI applications in neuroimaging can extend to PET scans, where automated algorithms can support the detection of metabolic abnormalities, early neurodegenerative changes, and treatment response assessment [22, 29].

Speech and cognitive assessments Amini et al. developed a novel automated method leveraging natural language processing (NLP) and machine learning to predict AD progression from MCI using speech analysis. Utilizing neuropsychological test interviews from 166 participants of the Framingham Heart Study, the researchers transcribed and encoded speech data into quantitative features, subsequently training logistic regression models combined with demographic information (age, sex, education). Their model achieved an accuracy of 78.5%, with high sensitivity (81.1%) and specificity (75%) in predicting the progression from MCI to Alzheimer's within six years, surpassing the performance of traditional cognitive tests and the Mini-Mental State Examination (MMSE). This AI-driven speech analysis approach represents a promising non-invasive, cost-effective tool for early identification of dementia, potentially enhancing timely intervention strategies and patient outcomes [30].

In the study by Kaser et al., researchers developed an automated speech analysis algorithm to detect cognitive impairment among Spanish-speaking individuals. The study involved 174 participants categorized as cognitively normal (CN, n = 87), mild cognitive impairment (MCI, n = 63), or all-cause dementia (n = 24). Participants completed four language tasks: animal fluency, alternating fluency (sports and fruits), phonemic "F" fluency, and the Cookie Theft Description. These recordings

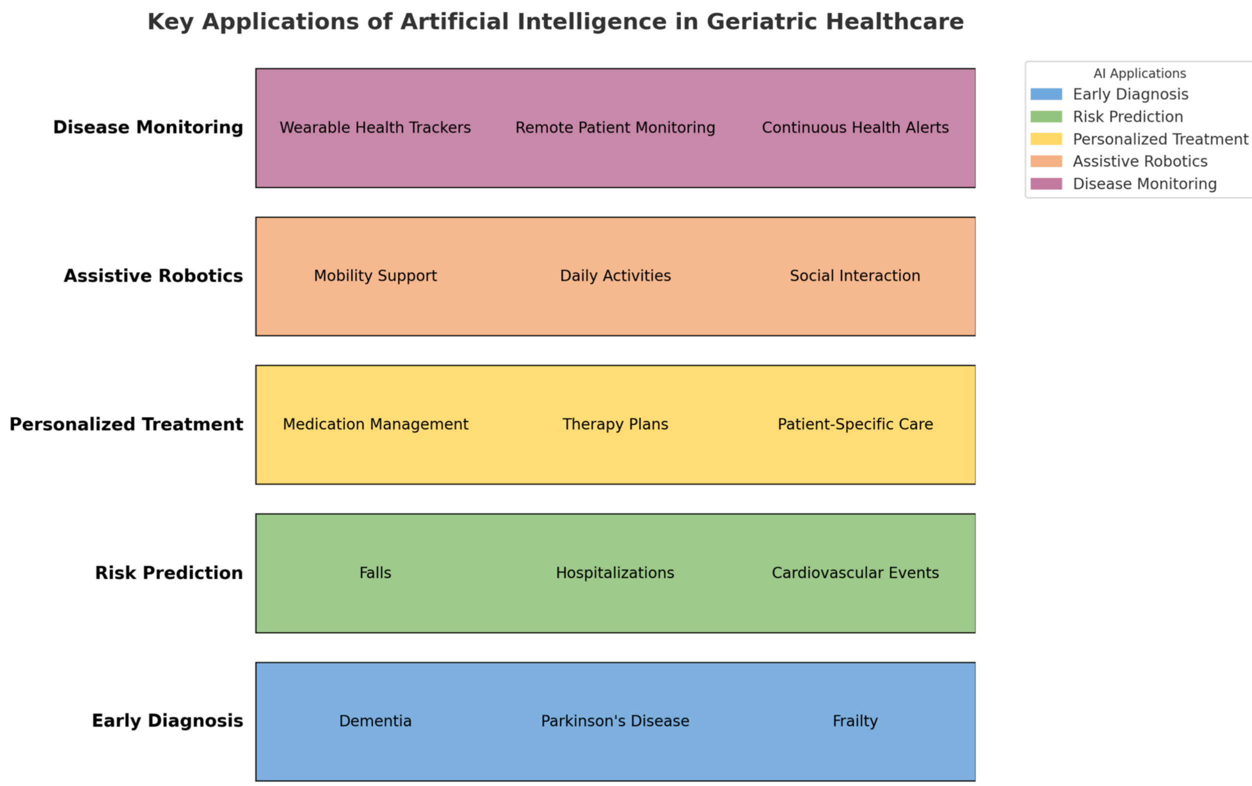

Fig. 2 Key Applications of Artificial Intelligence in Geriatric Healthcare. Illustration of the role of AI in geriatric healthcare, highlighting its applications in early diagnosis, risk prediction, personalized treatment, assistive robotics, and continuous disease monitoring. These domains rely on different AI techniques, such as supervised learning (e.g., logistic regression, decision trees, random forests, support vector machines), unsupervised learning (e.g., clustering, autoencoders), and reinforcement learning (e.g., Q-learning, deep reinforcement learning). Such methods are applied across healthcare to support predictive modeling, clinical decision-making, natural language processing, and computer vision for medical imaging and robotic assistance

were processed using text transcription and digital signal processing to extract neuropsychological and audio features. A training sample of 122 subjects was used to develop the algorithm, which was then tested on a demographically balanced subset of 52 participants. The algorithm effectively distinguished between CN and impaired (MCI + dementia) groups, achieving an area under the curve (AUC) of 0.93, with an overall accuracy of 88.4%, sensitivity of 87.5%, and specificity of 89.2%. When comparing CN to MCI groups, the algorithm yielded an AUC of 0.90, accuracy of 87.5%, sensitivity of 83.3%, and specificity of 89.2%. These findings suggest that automated speech analysis can serve as a viable screening tool for cognitive impairment in Spanish-speaking populations [31].

Gait and facial expression analysis Recent AI advancements have also demonstrated significant potential in diagnosing neurodegenerative diseases through the analysis of gait patterns and facial expressions.

Jing et al. developed a noninvasive, contactless gait assessment method to support early diagnosis of neurodegenerative diseases (NDDs). Using an Azure Kinect 3D camera, researchers collected motion data from 41 participants aged 25–85, analyzing gait patterns with machine learning classifiers, specifically a SVM and a bidirectional long short-term memory (Bi-LSTM) model. The Bi-LSTM significantly outperformed the SVM, achieving an average precision of 90.54%, recall of 90.41%, and an F1-score of 90.38%, versus SVM's precision of 86.99%. The Bi-LSTM model also provided superior gait segmentation accuracy (93.2%) and lower gait parameter calculation errors (3.17%) compared to traditional methods. This study highlights the effectiveness of deep learning approaches for accurate, comfortable, and efficient gait assessment, facilitating earlier diagnosis and better clinical management of NDDs [32].

Furthermore, Goudarzi et al. have highlighted the AI-driven recognition and classification of facial expressions can facilitate early detection of neurological disorders, particularly neurodegenerative diseases such as Alzheimer's and Parkinson's. By employing deep learning and computer vision techniques, the authors suggest that these techniques can accurately interpret subtle facial expression changes associated with these conditions [33].

Cardiovascular diseases

Cardiovascular diseases (CVD) represent a major cause of morbidity and mortality in older adults, significantly impacting their quality of life. AI technologies are rapidly transforming the clinical management of these conditions, enhancing diagnostic precision, predictive accuracy, and personalized patient care.

Arrhythmias and AI Atrial fibrillation (AF) is the most common cardiac arrhythmia among older adults, with prevalence significantly increasing with age. It affects approximately 10% of individuals aged 80 years or older, representing a major risk factor for ischemic stroke, heart failure, and mortality in elderly populations. Due to its often asymptomatic nature in older individuals, AF frequently remains undiagnosed until complications arise, underscoring the critical need for early detection and intervention in geriatric healthcare [34].

Some authors developed and validated an AI-enabled ECG algorithm designed to detect AF from ECG recordings acquired during normal sinus rhythm. This retrospective study analyzed ECG data from 180,922 patients, training a deep neural network model to recognize subtle ECG changes predictive of AF episodes. The algorithm demonstrated a high predictive accuracy, achieving an area under the receiver operating characteristic curve (AUC) of 0.90 (95% CI: 0.90–0.91), with sensitivity of 82.3% (80.9–83.6) and specificity of 83.4% (83.0–83.8). These results indicate that AI-enhanced ECG analysis can effectively identify individuals at high risk of AF, even before clinical manifestations, facilitating timely preventive interventions [35].

Heart failure and AI Heart failure (HF) remains one of the leading causes of hospitalization among older adults, characterized by frequent exacerbations and hospital readmissions. Recent therapeutic advancements, including sodium-glucose co-transporter 2 (SGLT2) inhibitors and finerenone show promising effects in reducing hospitalizations and disease progression, especially in older populations with comorbidities such as chronic kidney disease. Integrating AI into clinical practice could enhance HF management by enabling early detection of exacerbations and personalized risk stratification, ultimately aiming to decrease readmission rates and improve outcomes in elderly patients [36]. In the study conducted by Adler et al., researchers leveraged ML techniques, specifically boosted decision trees, to enhance the prediction of mortality risk among HF patients. The study analyzed clinical data from 5,822 HF patients, including both hospitalized and ambulatory individuals. Eight key variables, both laboratory and clinical, emerged as highly predictive: creatinine levels, blood urea nitrogen, hemoglobin concentration, red blood cell distribution width, white blood cell count, platelet count, serum albumin, and clinical parameters such as diastolic blood pressure. The ML- based model demonstrated superior predictive performance with an AUC of 0.88, outperforming traditional HF risk prediction methods. External validation performed on two independent HF cohorts further confirmed the robustness and generalizability of the model, achieving AUCs of 0.84 and 0.81, respectively. These findings underscore the potential of machine learning algorithms to significantly improve the accuracy and clinical utility of risk stratification tools in heart failure management [37].

Coronary artery disease (CAD) and AI-based risk stratification models Coronary artery disease (CAD) is highly prevalent in older populations and can present atypically, complicating early diagnosis. AI-based risk stratification models employing machine learning have successfully predicted CAD events using clinical history, lifestyle factors, and biomarker analysis. For instance, Motwani et al. investigated the AI algorithm's efficacy in predicting major adverse cardiac events (MACE) by analyzing cardiac computed tomography angiography (CCTA) scans. The study encompassed 10,030 patients with suspected coronary artery disease (CAD) who underwent CCTA as part of the COronary CT Angiography EvaluatioN For Clinical Outcomes: An InteRnational Multicenter (CONFIRM) registry. Over a five-year follow-up period, 745 patients experienced all-cause mortality. The researchers applied machine learning techniques, specifically a boosted ensemble algorithm, to integrate 25 clinical and 44 CCTA parameters. Key variables included segment stenosis score (SSS), segment involvement score (SIS), modified Duke index (DI), number of segments with different plaque types, age, sex, and standard cardiovascular risk factors like hypertension and diabetes. The machine learning model demonstrated superior predictive performance for five-year all-cause mortality, achieving an AUC of 0.79. This performance was significantly higher compared to traditional risk assessment tools: Framingham risk score (AUC: 0.61), SSS (AUC: 0.64), SIS (AUC: 0.64), and DI (AUC: 0.62), all $P < 0.001$ [38].

These findings suggest that AI algorithms, when applied to comprehensive clinical and imaging data, can enhance the prediction of adverse cardiac events, potentially leading to improved patient management and outcomes.

Hypertension management Hypertension is a prevalent CV risk factor among older adults, significantly associated with increased morbidity and mortality due to complications such as stroke, coronary artery disease, and chronic kidney disease [39]. Effective blood pressure control remains challenging in elderly populations due to factors like multimorbidity, polypharmacy, variability in drug responses, and difficulty adhering to treatment regimens. AI offers innovative approaches to tackle these challenges, particularly through personalized medicine strategies [40].

AI-driven personalized management systems have demonstrated substantial potential in optimizing antihypertensive treatments by analyzing extensive clinical datasets and demographic characteristics to accurately predict individual patient responses to specific medications. In their 2018 study, Ye et al. developed and prospectively validated a ML model to predict the onset of hypertension within one year, utilizing EHRs from the Maine Health Information Exchange network. The study included a retrospective cohort of 823,627 individuals from 2013 and a prospective cohort of 680,810 individuals from 2014. The model employed the XGBoost algorithm, which is known for its high performance in classification tasks. The model achieved AUCs of 0.917 in the retrospective cohort and 0.870 in the prospective cohort, indicating excellent predictive accuracy. Risk scores generated by the model stratified individuals into five categories, with the highest risk group showing a 50.93% incidence of hypertension within the following year. Key predictors included type 2 diabetes, lipid disorders, cardiovascular diseases, mental illnesses, healthcare utilization metrics, and socioeconomic factors. Notably, individuals over 50 with multiple chronic conditions, especially those on medications for mental disorders, were at elevated risk. The study underscores the potential of ML in leveraging EHR data to identify individuals at high risk for hypertension, facilitating early interventions and personalized care strategies [41].

Further research has reinforced these findings, demonstrating AI's ability to incorporate genetic markers, lifestyle data, and continuous monitoring inputs (e.g., from wearable devices) to dynamically adjust therapeutic plans and enhance patient adherence. Such comprehensive, individualized approaches offer the promise of better hypertension control, fewer adverse drug events, reduced cardiovascular risks, and improved overall quality of life for older adults [42].

Chronic disease prevention and monitoring

Prevention is crucial in geriatric healthcare, as the elderly are more susceptible to chronic conditions such as diabetes, retinopathy, cancer and chronic respiratory diseases. AI models can aid in predicting the onset of these conditions and identifying at-risk individuals, allowing for early intervention and prevention strategies.

Pan et al. conducted a bibliometric analysis to assess the application of AI in chronic disease health management, aiming to identify research trends and provide insights into the field's current state. The study analyzed 341 publications from 775 institutions across 55 countries, published in 175 journals by 2,128 authors. A significant increase in publications was observed between 2013 and 2024, accounting for 95.31% of the total output. The analysis identified four primary research clusters: diagnosis, care, telemedicine, and technology. Recent trends highlighted mobile health technologies and ML as key focal points in AI applications for chronic disease management. Despite advancements, challenges such as improving research quality, fostering international collaboration, standardizing data-sharing practices, and addressing ethical and legal concerns persist. The study emphasizes the need for global partnerships to enhance AI integration into clinical practice for more effective chronic disease management [43].

Moreover, advancements in computer vision have significantly improved the early diagnosis of age-related conditions. AI-driven models, especially those utilizing DL techniques such as convolutional neural networks (CNNs), have demonstrated high accuracy in analyzing medical imaging, allowing for early detection and intervention in diseases like age-related macular degeneration (AMD), diabetic retinopathy, and neurodegenerative disorders. These technologies enhance traditional diagnostic workflows by automating image interpretation, reducing subjectivity, and improving efficiency in large-scale screening programs.

A systematic review and meta-analysis assessed the AI effectiveness of AI in detecting AMD from color fundus photographs. The study analyzed 19 research papers, with 13 included in the quantitative synthesis, all using human graders as the reference standard. The findings indicated that AI demonstrated high diagnostic accuracy, with a pooled area under the receiver operating characteristic curve (AUROC) of 0.983, a sensitivity of 0.88, and a specificity of 0.90. The diagnostic odds ratio was 275.27, further reinforcing AI's reliability in AMD detection. A threshold analysis identified a potential threshold effect, contributing to study heterogeneity. Specifically, studies employing CNNs trained on the Age-Related Eye Disease Study (AREDS) database reported a pooled AUROC of 0.983, sensitivity of 0.88, specificity of 0.91, and a diagnostic odds ratio of 273.14. These results underscore the potential of AI-based tools to enhance early detection and management of AMD, offering a promising approach to mitigating vision loss associated with aging. However, challenges such as dataset diversity, model generalizability, and clinical integration must be addressed to ensure widespread adoption of AI in ophthalmology [44].

Personalized care for the elderly

The heterogeneity of health conditions among elderly individuals underscores the importance of personalized care. AI can help customize treatment plans, ensuring that each patient receives the most appropriate interventions based on their individual health profile. With the elderly population often dealing with multiple health conditions, managing polypharmacy (the use of multiple medications) can be particularly complex.

Medication management and polypharmacy Managing polypharmacy, defined as the concurrent use of multiple medications, is a significant challenge in geriatric care, as it increases the risk of adverse drug reactions, drug–drug interactions, and medication non-adherence among older adults. AI can offer innovative solutions to address these complexities by analyzing extensive datasets to optimize medication regimens, predict potential adverse effects, and enhance overall medication safety [45].
Recent studies have demonstrated AI's potential in this domain. Rao et al. investigated the potential of large language models (LLMs), specifically ChatGPT 3.5, in managing polypharmacy among older adults. Using standardized clinical vignettes, the study evaluated the model's ability to recommend deprescribing in complex patient scenarios. ChatGPT consistently suggested stopping medications for patients without cardiovascular disease (CVD), regardless of their functional status, while its recommendations varied in those with a history of CVD. On average, the model recommended deprescribing 2.67 to 3.67 medications out of seven, with the number increasing as functional impairment worsened. However, the presence of CVD did not significantly influence the total number of medications suggested for discontinuation. The model also demonstrated a tendency to prioritize deprescribing pain medications over other drug classes. These findings suggest that LLMs could be integrated into clinical workflows to support decision-making in polypharmacy management, aligning in part with human clinical reasoning and potentially improving medication safety in older patients [46].

Another approach involved using knowledge graph embedding techniques to predict polypharmacy side effects. By modeling drug pairs and their associated side effects as a knowledge graph, AI algorithms can learn vector representations of drugs and side effects, enabling the prediction of unknown drug–drug interaction side effects. This method has shown improved performance over previous models, highlighting AI's capability to enhance the prediction of adverse drug reactions in polypharmacy contexts [47].

Sirois et al. developed a protocol to leverage AI for identifying and managing polypharmacy risks among older adults in Quebec, integrating data from the Quebec Integrated Chronic Disease Surveillance System. Their approach combined AI-driven pattern recognition with public health and ethical considerations. The study aimed to develop predictive models that identify high-risk polypharmacy cases based on medication history, health outcomes, and sociodemographic factors. By analyzing over 20 years of healthcare data, their methodology sought to generate clinically relevant polypharmacy indicators that could improve patient safety and inform public health strategies. A key aspect was ensuring the ethical deployment of AI, addressing biases in model training and the social acceptability of AI-generated recommendations. The research underscores AI's potential to enhance polypharmacy management through real-world data integration, offering a proactive approach to reducing adverse drug events in the elderly population [48]. More recently, AI-driven CDSS have been developed to assist healthcare professionals in managing polypharmacy. Martins et al. introduced a CDSS designed to address the challenges of polypharmacy in healthcare settings. The system focuses on identifying potential herb–drug interactions and instances of prescription drug abuse by integrating an expert knowledge base with supervised ML models. Furthermore, the system provides user-friendly alerts to pharmacists, enhancing their ability to make informed decisions regarding medication management. Through simulated scenarios using de-identified patient information, the study demonstrated a significant capability to improve pharmaceutical care, safeguard patient data, and support pharmacists in optimizing medication regimens. The implementation of such AI-driven solutions can be useful in mitigating the risks associated with polypharmacy, particularly among older adults who are more susceptible to adverse drug interactions [49].

Rehabilitation and physical therapy AI is transforming rehabilitation for elderly individuals recovering from surgeries, strokes, or falls by optimizing therapy regimens, enhancing patient monitoring, and improving recovery outcomes. AI-powered ML models can analyze patient data to create personalized rehabilitation plans, continuously adjusting exercises based on progress and minimizing the risk of complications [50]. Wearable devices equipped with AI capabilities can play a crucial role in monitoring patient movements during physical therapy sessions. These devices can track metrics such as range of motion, gait patterns, and activity levels, providing real-time feedback to both patients and healthcare providers. This continuous monitoring allows for immediate adjustments to therapy exercises, promoting optimal recovery and reducing the risk of injury [51–53].
Additionally, the integration of virtual reality (VR) and socially assistive robots (SARs) into rehabilitation programs has shown promising results in motivating patients and improving long-term engagement with therapy. AI-driven predictive analytics further enhance rehabilitation by identifying key recovery indicators, allowing clinicians to adjust interventions proactively based on

expected patient outcomes [54, 55]. Despite its potential, challenges remain, including data privacy concerns, integration into existing healthcare infrastructures, and ensuring accessibility for elderly users. However, as AI-driven rehabilitation tools continue to evolve, they offer a promising avenue for more efficient, personalized, and adaptive recovery strategies in geriatric healthcare [56].

In the context of rehabilitation therapy for stroke survivors, aiming to enhance motor function recovery through adaptive and personalized interventions, recent studies have highlighted potential challenges in implementing RL-based therapies during the sub-acute phase post-stroke.

A study by Branscheidt et al. investigated the capacity for RL in stroke patients at different recovery stages. The research compared two groups: one assessed within three months post-stroke (early group) and another evaluated after six months (late group). Findings revealed that RL was notably impaired in the early group, while error-based learning remained unaffected in both cohorts. This suggests that the ability to benefit from RL-driven rehabilitation may be compromised during the initial months following a stroke.

These insights have significant implications for designing rehabilitation programs. They indicate that RL-based interventions might be more effective if introduced during the chronic phase of stroke recovery, rather than the sub-acute phase. Adjusting the timing of such therapies could optimize patient outcomes by aligning intervention strategies with the patient's learning capabilities during different recovery stages [57]

Fall prediction and prevention Falls are a leading cause of injury and death in the elderly, and predicting falls before they happen is a critical challenge [58, 59]. Several scoring systems have been developed to predict the risk of falls in older adults, including the Morse Fall Scale (MFS), the Hendrich II Fall Risk Model, and the Stopping Elderly Accidents, Deaths, and Injuries (STEADI) algorithm. These tools assess various risk factors such as gait instability, cognitive impairment, previous falls, medication use, and environmental hazards. While they provide useful clinical guidance, they have several limitations. Many traditional fall risk scores rely on subjective clinician assessments, which can introduce variability and reduce reproducibility. Additionally, these tools often lack real-time adaptability, failing to account for dynamic changes in a patient's condition. Furthermore, some models demonstrate limited predictive power due to insufficient weighting of key risk factors or an overemphasis on categorical variables rather than continuous risk profiling [60, 61].

In contrast, AI-based fall risk prediction models offer several advantages. ML algorithms can analyze vast datasets, incorporating real-time physiological data from wearable sensors, EHRs, and motion analysis systems to provide more personalized risk assessments. AI can identify subtle movement patterns and emerging fall risks that may be overlooked by traditional scoring methods. Furthermore, AI-driven models can continuously learn and adapt, refining their predictions based on new data, which allows for earlier intervention and improved fall prevention strategies. This transition from static risk scores to dynamic, AI-enhanced predictive models has the potential to significantly reduce fall-related injuries and hospitalizations in geriatric populations [62].

Jahandideh et al. investigated the effectiveness of ML models in predicting falls among hospitalized adults, utilizing EHRs to enhance fall risk assessment. The study applied RF and DNN algorithms to identify significant predictors of falls, achieving high predictive performance. The DNN model reported an accuracy of 0.988 and specificity of 0.999, while the RF model demonstrated an accuracy of 0.989 and specificity of 1.000. Key risk factors identified included patient-related variables (age, mobility status, comorbidities), staffing-related aspects (nurse-to-patient ratios, staff experience), and admission-related factors (reason for hospitalization, length of stay). The results highlight the potential of ML-driven predictive tools in hospital settings, offering a data-driven approach to enhance fall prevention strategies. By integrating these models into clinical workflows, hospitals can proactively identify high-risk patients and implement targeted interventions, potentially reducing fall-related injuries and healthcare costs. However, further validation across diverse patient populations is necessary to ensure broader applicability and effectiveness in real-world healthcare settings [63].

These results are consistent with those of the study by Shao et al., further confirming the effectiveness of AI and machine learning in fall prevention. As mentioned before, the authors developed and validated a ML-based fall prediction model for nursing home residents, identifying six key predictors (balance, grip strength, fatigue, fall history, age, and comorbidity). The model showed good predictive accuracy (ROC-AUC: 0.710–0.750), balancing sensitivity and specificity effectively. The resulting nomogram provides a practical clinical tool to assist caregivers in identifying residents at high risk, facilitating timely interventions to prevent falls [28].

Frailty predictions Frailty, a syndrome characterized by decreased physiological reserve, is a major risk factor for morbidity and mortality in older adults [64].

Various ML approaches have been explored for frailty screening, with SVMs emerging as one of the most frequently utilized techniques. SVMs have demonstrated promising results in the early detection of frailty by effectively classifying individuals based on clinical and physiological data. These models excel in identifying complex, non-linear relationships within datasets, making them particularly useful for detecting subtle frailty patterns that may not be evident with traditional screening methods. However, despite their potential, challenges remain, particularly regarding data quality. Frailty assessments often rely on heterogeneous datasets collected from different sources, including self-reported questionnaires, clinical records, and wearable sensor data. Variability in data formats, missing values, and inconsistencies in frailty definitions can impact the performance and generalizability of ML models. Addressing these challenges through standardized data collection protocols and improved preprocessing techniques will be crucial for enhancing the reliability of ML-driven frailty screening in clinical practice [65].

Sajeev et al. explored the use of ML models for identifying pre-frailty in community-dwelling older adults, aiming to improve early detection and targeted interventions. The study analyzed data from 656 participants aged 40–75 years, incorporating physiological, anthropometric, environmental, social, and lifestyle factors. The ML models demonstrated strong predictive performance, achieving an AUC of up to 0.817 when using the Fried Frailty Phenotype (FFP) and 0.722 with the Clinical Frailty Scale (CFS). Key predictors of pre-frailty included higher body mass index (BMI), lower muscle mass, reduced grip strength, impaired balance, elevated distress levels, poor sleep quality, shortness of breath, and incontinence. These findings reinforce the potential of ML-driven screening tools in identifying individuals at risk of frailty at an early stage, allowing for timely intervention strategies. The study highlights the necessity of integrating diverse health metrics into ML models to enhance accuracy and applicability in clinical and community settings [66].

Another study reviewed existing literature on ML applications for frailty syndrome and assessed various frailty measurement tools used in clinical practice. The authors highlighted the potential of ML algorithms in analyzing both physical and psychosocial domains of frailty, suggesting that such approaches could assist healthcare professionals in tailoring and optimizing treatment and care for patients with HF. The study also presented an exemplary application of ML for frailty assessment based on the Tilburg Frailty Indicator (TFI) questionnaire, emphasizing the importance of incorporating psychosocial variables into predictive models [67].

The impact of a hybrid exercise program on frailty reversal and physical fitness in older adults, incorporating ML to predict intervention outcomes has been evaluated recently in a randomized controlled trial including 181 community-dwelling frail individuals aged 65 and older, who were assigned to one of three exercise groups: Wu Qin Xi (WQX, a traditional Chinese exercise), Strength and Endurance (SE) training, or a combined Hybrid Exercise (WQXSE) group. The 24-week intervention assessed changes in frailty status, mobility, grip strength, and walking speed. The results demonstrated that 41.7% of participants reversed frailty status, with the highest improvement rates in the WQXSE (44.4%) and SE (43.9%) groups. The hybrid approach significantly improved walking speed and grip strength, suggesting that integrating traditional and modern training techniques may be beneficial for frail older adults. Additionally, ML models, particularly the stacking algorithm, effectively predicted frailty reversal outcomes, highlighting their potential in tailoring personalized exercise interventions [68].

The role of AI in reducing hospital readmissions among older adults Hospital readmissions pose a significant challenge in modern healthcare, particularly among older adults and patients with chronic conditions. Unplanned readmissions not only increase healthcare costs but also indicate gaps in patient management and continuity of care [69]. Identifying individuals at high risk for readmission and implementing targeted interventions is crucial for improving patient outcomes and optimizing hospital resource utilization.

Romero-Brufau et al. investigated the implementation of an AI-based clinical decision support system to reduce unplanned hospital readmissions at a regional hospital. The AI tool was deployed in a regional hospital in La Crosse, Wisconsin, between November 2018 and April 2019, assessing all admitted patients for readmission risk and generating intervention recommendations. Similar hospitals were used as controls to evaluate the impact of AI implementation. Among 2,460 evaluated hospitalizations, 611 were classified as high-risk cases. The AI model demonstrated a sensitivity of 65% and specificity of 89% in identifying at-risk patients. Following the implementation of the AI-based tool, the readmission rate decreased from 11.4% in the pre-intervention period to 8.1% ($p < 0.001$). After adjusting for a 0.5% reduction in readmission rates observed in control hospitals (from 9.3% to 8.8%), the relative reduction in readmission rates was calculated at 25% ($p < 0.001$). These findings highlight the effectiveness of AI-driven predictive models in reducing hospital readmissions by enabling early identification of high-risk patients and facilitating targeted care interventions.

This study underscores the potential of AI-based decision support systems in improving patient outcomes and optimizing hospital resource allocation. The significant reduction in readmission rates suggests that AI can serve as a valuable tool in enhancing healthcare efficiency and mitigating preventable hospitalizations. However, further research is necessary to validate these findings across different healthcare settings and ensure the scalability and sustainability of AI-assisted interventions. [70].

Healthcare Management and Administration

AI is increasingly pivotal in enhancing healthcare management and administration, particularly in geriatric care, by alleviating healthcare providers' workload and improving care delivery efficiency for elderly patients.

Virtual assistants and Chatbots

AI-powered virtual assistants and chatbots are being utilized to support elderly patients in managing their healthcare needs. These systems offer medication reminders, assist with scheduling appointments, answer medical inquiries, and provide conversational engagement, thereby promoting patient independence and reducing healthcare providers' workload. For instance, a study highlighted the potential of chatbots in aiding patients with chronic conditions like diabetes, suggesting that such tools can enhance self-management and health outcomes. Additionally, research has emphasized the importance of designing voice assistants tailored to older adults to improve healthcare management and quality of life.

Wu et al. conducted a systematic review and meta-analysis to evaluate the effectiveness of chatbots in aiding diabetes self-management. The study analyzed 25 articles, encompassing system design studies (32%), pilot studies (32%), and intervention studies (36%). The meta-analysis revealed that chatbot interventions significantly reduced blood glucose levels (mean difference 0.30, 95% CI 0.04–0.55; $P = 0.02$), although they did not have a significant impact on weight reduction (mean difference 1.41, 95% CI −2.29 to 5.11; $P = 0.46$). The authors concluded that while chatbots show promise in supporting diabetes self-management, higher-quality research, such as randomized controlled trials, is necessary to strengthen the evidence base [71].

Care coordination and resource management

In long-term care facilities and home healthcare settings, AI assists in managing patient information, optimizing staffing schedules, and coordinating care. AI systems monitor patients' daily health status, alerting caregivers to potential issues to ensure timely interventions. Moreover, AI aids in managing hospital or nursing home bed occupancy, thereby enhancing operational efficiency [72]. Predictive models forecast patient care needs, facilitating better resource allocation and improving care quality. For example, a study discussed the development of person-centered, digitally enabled care pathways that integrate AI to manage multimorbidity in patients, highlighting AI's role in care coordination. Furthermore, AI-powered tools have been proposed to enhance mobility and function in older adults, demonstrating AI's potential in managing chronic conditions and maintaining independence [72, 73].

Additional domains of AI application in geriatrics could include medication management and healthcare access optimization. AI-based systems could perform formulary checks at the time of prescribing, automatically verifying whether a medication is covered by the patient's insurance plan to expedite treatment initiation [45, 46, 49]. Similarly, natural language processing tools may assist in the automated generation of discharge letters, appeal letters, or letters of medical necessity, thereby reducing the administrative burden and streamlining clinicians' workflows [3, 6]. Finally, the COVID-19 pandemic underscored the difficulties many elders experienced in scheduling vaccination appointments including those for influenza, pneumococcal disease, and herpes zoster; in comparable scenarios, AI could be deployed to facilitate real-time scheduling, notification, and navigation support, ensuring timely access to preventive services [46, 64].

In preventive screening, AI has shown great promise in colorectal cancer screening, with advanced algorithms enhancing polyp detection and characterization during colonoscopy, thereby lowering the risk of interval cancers [74].

Challenges and Ethical Considerations in AI Implementation for Geriatric Healthcare

While AI offers transformative potential in geriatric healthcare, its implementation is fraught with several challenges and ethical concerns. Ensuring that AI-driven solutions are both effective and equitable requires addressing multiple barriers, ranging from technological accessibility to data security and algorithmic fairness.

Technology adoption and accessibility

One of the primary challenges in integrating AI into geriatric healthcare is the limited digital literacy among older adults. Many elderly individuals face difficulties in using digital tools due to cognitive impairments, reduced vision, hearing loss, and motor limitations. Older adults often struggle with the usability of healthcare technology, requiring personalized interfaces and simplified interactions to encourage adoption. Furthermore, cognitive decline associated with aging may impact their ability to engage with AI-driven systems effectively, necessitating intuitive designs and caregiver-assisted implementations [75]. Addressing these accessibility barriers is essential to ensuring that AI-driven healthcare tools provide meaningful benefits rather than exacerbating disparities.

Data privacy and security

AI systems rely on vast amounts of patient data, making privacy and security critical concerns. In geriatric care, where medical histories are extensive and often complex, safeguarding sensitive health information from breaches is paramount. Regulations such as the Health Insurance Portability and Accountability Act (HIPAA) in the U.S. and the General Data Protection Regulation (GDPR) in the EU provide legal frameworks to protect patient data, but ensuring compliance within AI-driven healthcare applications remains challenging. ML models can inadvertently expose private health information if not adequately safeguarded [76]. Moreover, reliance on cloud-based storage and remote AI processing introduces additional vulnerabilities, necessitating robust encryption, access control measures, and continuous monitoring to prevent unauthorized access.

Bias and fairness

AI algorithms are only as reliable as the data they are trained on, and older adults are often underrepresented in clinical trials and datasets used for AI model development. This underrepresentation can lead to biased AI systems that fail to adequately address the unique health challenges of the geriatric population. Biased training data in AI models used for healthcare risk prediction can disproportionately underestimate the needs of some patient groups, leading to inequitable outcomes [77]. In the context of geriatric medicine, similar biases could result in the under-diagnosis of conditions such as frailty, cognitive decline, or polypharmacy-related risks. To mitigate these biases, AI models must be trained on diverse and representative datasets that include older adults with varying degrees of health conditions, socioeconomic backgrounds, and comorbidities.

Acceptance of AI technologies among elderly patients

Several recent studies have explored older adults' and caregivers' attitudes toward AI-driven healthcare tools. For example, perceptions were heterogeneous across groups of older adults. While some individuals were less likely to act on AI-generated medication advice compared to recommendations from healthcare professionals, Black American participants showed comparatively greater acceptance of AI-based guidance [78]. Focus group and survey data reveal a good level of acceptability for AI-supported features like appointment reminders and health monitoring, but also highlight concerns about privacy, usability, and dependency on technology [79].

Human-AI interaction and ethical decision-making

Another ethical concern involves the degree of autonomy granted to AI in clinical decision-making. While AI can assist in diagnostics and patient monitoring, it should not replace human clinical judgment, particularly in complex cases that require nuanced decision-making. Ethical guidelines emphasize that AI should serve as a decision-support tool rather than an autonomous decision-maker, ensuring that healthcare professionals retain oversight and accountability. AI should be used to augment rather than replace human expertise, promoting a collaborative approach that integrates AI recommendations with physician assessments [80].

A promising avenue for AI is its potential to assist in determining the appropriate timing for transitioning patients to hospice or palliative care. In addition, AI could play a role in supporting brain death determination, a process for which considerable variability in diagnostic approaches still exists. By integrating and analyzing multimodal clinical and imaging data, AI systems may provide, in the future, a more consistent and evidence-based assessment of the likelihood of brain death [81].

Table 1 provides an overview of the benefits and challenges associated with AI applications in geriatric healthcare, highlighting their potential impact and implementation barriers.

Future directions

To address the challenges of AI in geriatric healthcare, several strategies should be considered:

- Improving AI Accessibility: AI tools should be designed with user-friendly interfaces, voice-activated commands, and caregiver integration to accommodate older adults with varying levels of digital literacy.
- Enhancing Data Security: AI-driven healthcare systems must adopt advanced encryption techniques, blockchain technology for data integrity, and strict compliance with data protection laws.
- Ensuring Algorithmic Fairness: AI models should be trained on diverse datasets that adequately represent older populations, including those from different racial, ethnic, and socioeconomic backgrounds.
- Maintaining Human Oversight: AI should complement rather than replace human clinicians, with clear guidelines on its role in medical decision-making to avoid ethical and legal pitfalls.
- Ensuring equity in AI deployment. In lower-income communities, there is a risk that cheaper but less reliable AI systems may be implemented, potentially exacerbating existing health disparities. Ensuring that AI solutions are both accessible and of high quality will be essential to promote fairness and avoid widening gaps in care.

Table 1 Benefits and Challenges of AI Applications in Geriatric Healthcare [45–70]

AI Application	Description	Benefits	Challenges
Early Disease Detection	AI-driven imaging and biomarker analysis for detecting conditions like dementia, CV disease, and frailty	Early intervention, improved diagnostic accuracy	Requires high-quality datasets, risk of algorithmic bias
Fall Prevention	Machine learning models analyze gait patterns and predict fall risks in older adults	Reduces fall-related hospitalizations, enhances mobility safety	Integration into real-world settings, false positives
Frailty and Polypharmacy Management	AI predicts frailty progression and assists in managing medication interactions	Personalized treatment, reduced adverse drug reactions	Underrepresentation of older adults in training data, digital literacy issues
Rehabilitation and Assistive Robotics	AI-powered rehabilitation programs dynamically adjust therapy plans for stroke or post-surgical recovery	Enhances physical function, promotes independence	Cost of implementation, patient adherence
Remote Patient Monitoring (RPM)	Wearable devices and AI-driven health monitoring for chronic disease management	Reduces hospital visits, enables proactive care	Data security concerns, need for continuous monitoring infrastructure
Cognitive Health & Dementia Care	AI detects cognitive decline through speech analysis, facial recognition, and neuroimaging	Early diagnosis, personalized cognitive therapy plans	Ethical concerns in data collection, model validation
Hospital Readmission Prevention	Predictive analytics identify high-risk patients for targeted interventions	Reduces rehospitalizations, improves resource allocation	Requires integration into EHR systems
AI in Healthcare Administration	Chatbots, virtual assistants, and AI-driven scheduling systems optimize healthcare workflows	Reduces administrative burden, improves patient engagement	Privacy and cybersecurity risks, potential for misinterpretation of AI-generated recommendations

Key applications of AI in geriatric healthcare, highlighting their primary benefits and the associated challenges in implementation. AI-driven solutions are increasingly utilized for disease detection, fall prevention, rehabilitation, and healthcare administration, yet ethical, logistical, and technological barriers must be addressed for optimal integration into clinical practice. *CV* cardiovascular disease; *EHR* electronic health record

Conclusion

AI is revolutionizing geriatric healthcare by enhancing early disease detection, optimizing treatment plans, facilitating personalized interventions, and improving overall healthcare efficiency. The application of AI-driven predictive analytics, decision support systems, and robotic assistance has demonstrated significant potential in addressing key challenges in aging populations, such as multimorbidity, frailty, polypharmacy, and fall prevention. Moreover, AI-enabled tools are streamlining healthcare management, reducing hospital readmissions, and supporting independent living for older adults.

Despite these advancements, integrating AI into geriatric care presents several challenges, including data privacy concerns, digital literacy barriers, algorithmic biases, and ethical considerations in clinical decision-making. Ensuring that AI-driven solutions are inclusive, accessible, and ethically sound is paramount to their successful implementation in real-world healthcare settings.

Future research should focus on improving AI model transparency, expanding datasets to better represent diverse elderly populations, and fostering interdisciplinary collaboration between clinicians, data scientists, and policymakers. Additionally, efforts should be made to develop user-friendly AI applications tailored to the cognitive and physical needs of older adults, ensuring equitable access to technological advancements.

As AI technology continues to evolve, its role in geriatric healthcare will undoubtedly expand, offering new opportunities to enhance patient outcomes, reduce healthcare costs, and promote healthy aging. However, its implementation must be guided by rigorous scientific validation, ethical standards, and a patient-centered approach to truly transform the future of elderly care.

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Authors' contributions
C.T. and C.S. conceived the structure and wrote the main manuscript text. N.C. and T.M. contributed to the literature review and critical revisions. P.M., M.T., and L.M. provided expertise in clinical and methodological aspects, contributing to the discussion and interpretation of findings. W.W.-G. and M.A.G. revised the manuscript for intellectual content and language. F.C. supervised the project and provided final approval. All authors reviewed and approved the final version of the manuscript.

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Declarations

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