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REVIEW

Artificial Intelligence in Chronic Disease Management for Aging Populations: A Systematic Review of Machine Learning and NLP Applications

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Abstract: As China's elderly population grows rapidly and the aging society arrives, the number of elderly patients with chronic diseases (mainly including chronic cardiovascular and cerebrovascular diseases, respiratory diseases, etc) continues to increase, significantly impacting individuals, families, and society. Geriatric Chronic Disease Management in China faces multiple challenges, including unequal distribution of medical resources, lack of professional management teams, insufficient health education, improper medication management, inadequate psychological support, insufficient medical insurance coverage, and insufficient family support. The rise of artificial intelligence (AI) technology (eg, machine learning, deep learning, NLP, computer vision) offers possibilities for improving Geriatric Chronic Disease Management, including optimizing the distribution of medical resources, supplementing professional management teams, popularizing health education, optimizing medication management, enhancing psychological support, improving medical insurance efficiency and accuracy, and strengthening family support. However, the application of AI in Geriatric Chronic Disease Management still faces challenges such as the data scarcity, model generalization, clinician adoption, alignment of AI decision-making with clinical guidelines, Integration with existing healthcare systems, privacy and security, user acceptance, ethics and law. To overcome these challenges, interdisciplinary collaboration is needed to promote the rational and effective application of AI technology, aiming to achieve healthy aging. This paper systematically reviews the current status, challenges, and future directions of AI application in Geriatric Chronic Disease Management.

Keywords: aging society, geriatric chronic disease management, artificial intelligence technology

Introduction

Since China entered an aging society in 2000, when the population aged 65 and above reached 7%,[1] both the scale and proportion of the elderly population have generally shown an upward trend. The process of population aging has accelerated, and the trend toward a higher proportion of older adults is increasingly evident. The data from China's seventh national census in 2020 shows that the population aged 60 and above was 264 million, accounting for 18.7% of the total population, with those aged 65 and above numbering 191 million, representing 13.5% of the total population.[2] Compared to the sixth national census in 2010, the proportion of the population aged 60 and above increased by 5.44%, and the proportion of those aged 65 and above rose by 4.63%.[2] Over the ten-year period since 2010, the population aged 60 and above increased by 86.37 million, with a 5.44% increase in proportion,[2] whereas between 2000 and 2010, the elderly population increased by 47.67 million, only showing a rise of 3.23%.[3] It is evident that both the scale of the elderly population and the degree of population aging have accelerated over the past decade. According to data released by the National Bureau of Statistics of China in 2022, at the end of 2022, the population aged 60 and above was 280.04 million, accounting for 19.8% of the total national population. Among them, the population aged 65 and above was 209.78 million, making up 14.9% of the total national population.[4–6] According to the United Nations Standards (UN Population Division), An Ageing Society is defined as having ≥7% of its population aged 65 and older and ≥14% of population aged 65 and older is Aged Society. The ≥20% threshold is termed "Super-Aged Society".[7,8] Corresponding to

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the stages of population aging in China, by 2022, China had already entered an aged society, and it is projected that by 2031, it will enter a super-aged society.[7]

However, the ensuing increase in elderly patients with chronic diseases has significantly impacted the health of the senior population. According to the WHO core criteria (2021 update),[9] chronic diseases are defined as health conditions lasting ≥3 months that are not vaccine-preventable, generally non-self-limiting, and require ongoing management. According to the latest statistical data and research reports, the prevalence of chronic diseases among the elderly population in China exhibits several significant characteristics: Firstly, the prevalence rate of chronic diseases remains high. As of 2023, approximately 78% of the population aged 60 and above suffer from at least one chronic disease.[10] This data highlights the ubiquity of chronic diseases among the elderly and signifies that they have become a major threat to the health of older individuals. Secondly, the coexistence of multiple diseases is common. Among those aged 65 and above, about two-thirds suffer from multiple chronic conditions simultaneously.[11,12] This phenomenon not only severely affects the quality of life for the elderly but also poses a great threat to their physical health. Thirdly, there is a diversity of main types of chronic diseases. Common chronic diseases among the elderly include hypertension, diabetes, cardiovascular and cerebrovascular diseases, cancer, chronic obstructive pulmonary disease (COPD), and dementia, etc.[13] These diseases not only have high incidence rates but may also be interrelated, making treatment and management more complex.

Chronic diseases in the elderly have far-reaching impacts on individuals, families, and society. For the individual patients, chronic diseases can lead to pain, limited mobility, and a decline in the ability to take care of oneself, thereby affecting the quality of daily life. Long-term illnesses may also trigger psychological issues such as anxiety and depression.[14] For families, family members may need to invest a significant amount of time and energy to care for the elderly patient, affecting their work and life. Emotional fluctuations in chronic disease patients and changes in family roles can also bring psychological stress to family members.[15] For society, the high incidence rate of chronic diseases puts pressure on medical resources, affecting the fairness and efficiency of healthcare services. The treatment and management of chronic diseases require a substantial amount of medical resources, increasing the social medical costs.[16] Therefore, implementing effective chronic disease management and prevention strategies to improve the health levels of the elderly is of great significance for achieving healthy aging.

Deficiencies in Geriatric Chronic Disease Management

Geriatric Chronic Disease Management refers to a systematic and continuous healthcare intervention system for populations aged 60 and above, characterized by core objectives including delaying disease progression (eg, maintaining HbA1c <7.0%), reducing acute exacerbations (eg, limiting COPD flare-ups to <2 annually), and preserving functional status (eg, ADL score ≥60).[17] The essential components comprise multidisciplinary collaboration, personalized care plans based on Comprehensive Geriatric Assessment, and cross-setting care continuity, complemented by China's integrated Traditional Chinese Medicine-Western approaches, combined medical-nursing institutional models, and hierarchical diagnosis-treatment protocols. These interventions have benefited numerous elderly patients with chronic diseases.

However, Geriatric Chronic Disease Management in China is not optimistic. This is mainly manifested in the following aspects:

Uneven distribution of medical resources:[18,19] The uneven distribution of medical resources is reflected not only in hardware facilities but also in the accessibility and quality of medical services. In large cities and developed areas, hospitals usually have advanced medical equipment and technology, and doctors are highly skilled. However, in rural and remote areas, medical facilities are rudimentary, and the level of medical technology is limited; some basic medical services cannot even be provided. This disparity means that elderly people in rural and remote areas often need to travel long distances to receive the medical services they need, which not only increases their economic burden but may also result in delayed treatment, thereby exacerbating the deterioration of chronic diseases.

Lack of professional chronic disease management teams:[20,21] A professional chronic disease management team includes multidisciplinary professionals such as doctors, nurses, nutritionists, and psychologists. Currently, many medical institutions in China lack such interdisciplinary collaborative teams, leading to a lack of comprehensive care for elderly patients with chronic diseases. The shortage of specialized personnel means that the elderly do not receive effective guidance in disease prevention and early intervention, which in turn affects the overall effectiveness of chronic disease control.

Insufficient health education for the elderly:[22,23] Insufficient health education is reflected in various aspects, including the dissemination of knowledge about chronic diseases and the promotion of healthy lifestyles. Many elderly people lack understanding of the causes, symptoms, complications, and preventive measures of chronic diseases, making it difficult for them to adopt effective preventive actions in daily life. Additionally, due to the lack of systematic health education, elderly people often rely excessively on traditional beliefs and folk remedies, neglecting the importance of scientific treatment.

Consequences of improper medication management:[24,25] Improper medication management by the elderly can lead to increased drug side effects, reduced therapeutic effects, and even drug poisoning. Since the liver and kidney functions of the elderly decline, precise control of drug dosage is particularly important. Improper medication management not only affects the physical health of the elderly but may also increase medical costs and the burden of family care.

Impact of insufficient psychological support:[14] Chronic diseases that trouble the elderly over a long period can easily lead to psychological issues. Currently, medical institutions often focus on the diagnosis and treatment of the disease itself while ignoring the patient's psychological state. The lack of psychological support can lead to emotional depression, self-denial, and other psychological issues in the elderly, which in turn affect the treatment and management of chronic diseases.

Challenges of inadequate medical insurance coverage:[26,27] Despite continuous improvements in the medical insurance system, there are still gaps in coverage for certain groups, such as elderly people in rural areas. Issues such as low reimbursement rates and complicated reimbursement processes make it difficult for the elderly to afford high medical expenses, often leading them to forgo treatment or resort to irregular self-treatment, which is extremely detrimental to chronic disease management.

Dilemma of insufficient family support:[28,29] Against the backdrop of the "four-two-one" family structure and empty nesters, the problem of insufficient family support has become increasingly prominent. Due to various reasons, children are unable to provide enough care and attention, resulting in a lack of necessary family support for the elderly in managing chronic diseases. This sense of loneliness and helplessness not only affects the quality of life of the elderly but may also accelerate the progression of chronic diseases. Therefore, building a social support system and increasing family and societal attention to the management of chronic diseases in the elderly has become an urgent priority.

AI Technology in Geriatric Chronic Disease Management

However, with the rise of AI technology, the aforementioned issues about Geriatric Chronic Disease Management are expected to be solved to some extent.

Artificial Intelligence (AI) is emerging as a transformative force in modern healthcare, harnessing advanced computational techniques to analyze complex medical data, identify patterns, and support clinical decision-making. At its heart, AI includes machine learning algorithms that improve over time through experience, natural language processing (NLP) that facilitates human-computer interaction, computer vision for the analysis of medical images, and predictive analytics for risk assessment.[30] These technologies are particularly valuable in geriatric care, where they can process vast amounts of heterogeneous health data — from electronic health records to wearable device outputs — to generate actionable insights. The fundamental strength of AI lies in its ability to perform repetitive tasks with superhuman consistency and to detect subtle patterns that might elude human clinicians. When properly implemented, AI systems serve as powerful decision support tools that augment rather than replace human expertise, fostering a collaboration between clinicians and AI that enhances the quality of care. This is especially pertinent in chronic disease management, where AI's capabilities in continuous monitoring, personalized intervention suggestions, and predictive risk stratification are well-suited to address the complex needs of an elderly population with multiple comorbidities.

This comprehensive review examines six key AI technologies that are reshaping geriatric care, each with its own set of strengths and limitations. Machine learning prediction models for diabetes risk stratification in rural Chinese populations have demonstrated strong performance (AUC 0.89–0.93), but are constrained by data quality requirements and interpret ability challenges.[31] NLP systems have shown clinically significant improvements in medication adherence (increased by 32%) and health literacy (increased by 25%), yet face adoption barriers such as dialect recognition limits (accuracy not exceeding 85%) and technophobia among the elderly.[32] Computer vision applications have achieved outstanding results in fall detection sensitivity (92%) and accuracy in rehabilitation exercises (88%), despite privacy concerns and high equipment costs.[33,34] Reinforcement learning algorithms have optimized treatment plans, resulting in better hypertension control (increased by 18%) and a reduction in adverse drug events (decreased by 40%), but require real-time biosensor data and have limited clinical validation sample sizes (less than 300).[35] Federated learning has enabled GDPR-compliant multi-center collaboration, with a 15% improvement in model performance, despite computational overhead and data standardization hurdles.[36] Affective computing tools show concordance with PHQ-9 in depression screening, although their effectiveness varies across different cultural expressions of emotion.[37] Overall, these technologies reveal a trade off between efficacy and practicality: while computer vision and machine learning achieve over 90% accuracy, they demand significant resources, whereas patient-facing tools like NLP require careful cultural adaptation. The findings underscore the need for context-specific implementations that balance technological capabilities with clinical realities in geriatric care settings.

Comparative Performance Analysis: The Table 1 below summarizes the technical specifications and clinical performance metrics of these AI applications:

Solutions to the Deficiencies in Geriatric Chronic Disease Management Provided by AI

Improving the uneven distribution of medical resources: AI can bridge the gap between urban and rural medical resources by allowing elderly individuals in rural and remote areas to access services from medical experts in large cities through video consultations and remote diagnosis via telemedicine platforms. The Nordic countries, renowned for their highly developed healthcare systems and innovative technological environments, have successfully integrated Artificial Intelligence (AI) with the Internet of Things (IoT) to promote remote monitoring in the medical field, especially in addressing the challenges of an aging society and uneven distribution of medical resources. For instance, the Wallenberg AI, Autonomous Systems and Software Program (WASP) in Sweden, a key innovation engine in the Nordic region, has supported the development of AI-powered remote monitoring systems.[48] These systems can analyze patients' health data in real-time, assisting doctors in remote diagnosis and treatment plan adjustments. In Finland, the telecommunications operator Elisa has collaborated with NetEase AI to launch an AI-based video monitoring solution. This solution utilizes real-time video analysis and AI algorithms to monitor patients' vital signs and behavioral patterns,

Table 1 Comparative Analysis of AI Technologies in Chronic Disease Management for Aging Populations

AI Technology	Application Scenario	Technical Methods	Empirical Outcomes	Limitations	Key References
Machine Learning (Predictive Models)	Diabetes risk prediction	- TabNet- Transformers	AUC 0.91–0.947-month prediction	- Data bias issues	[38,39]
Natural Language Processing (NLP)	Clinical text summarization	- BERT- GPT-3	92% ROUGE score	- Limited multilingual support	[40,41]
Computer Vision	Medical image segmentation	- Swin UNETR- nnUNet	99% tumor detection accuracy	- Requires expert annotation	[42]
Reinforcement Learning	Personalized cancer therapy	- SAC- PPO	25% survival rate improvement	- Small clinical trial sizes	[43]
Federated Learning	Cross-hospital data analysis	- FedProx- DP-SGD	18% F1-score improvement	- High communication overhead	[44,45]
Affective Computing	Depression screening	- Multimodal transformers	88% accuracy (vs PHQ-9)	- Cultural bias	[46,47]

providing a safe and reliable remote guardianship service for the elderly.[49] These cases demonstrate the significant achievements of the Nordic countries in the field of AI-powered remote health monitoring through policy support, technological innovation, and cross-industry collaboration. AI-assisted intelligent diagnostic systems deployed at primary healthcare institutions can enhance the accuracy and efficiency of diagnoses, reducing reliance on major city medical resources.

Supplementing professional chronic disease management teams: AI-powered health management assistants can provide personalized health management advice, including dietary, exercise, and medication guidance, thereby addressing the shortage of specialized professionals. For example, Lark Health utilizes AI to offer personalized health guidance for individuals with chronic conditions, such as diabetes management and hypertension control.[50] Their platform analyzes data from wearable devices and user inputs to provide tailored dietary, exercise, and medication recommendations, effectively supplementing the work of healthcare professionals. Through AI training platforms, a cohort of medical personnel with foundational knowledge in chronic disease management can be rapidly trained, thereby elevating the overall standard of medical services. For instance, the Cleveland Clinic in the United States collaborated with Microsoft to develop an AI-based training platform using virtual reality (VR) and simulations to train healthcare providers in handling various scenarios, including chronic disease management. Pilot studies of this platform have shown a 30% improvement in knowledge retention among trained healthcare providers.[51] Furthermore, companies like MedCognition are using AI-powered simulators for medical training. These simulators can replicate the physiological responses of real patients, allowing medical students to practice diagnosis and treatment in a safe, controlled environment, thereby enhancing their procedural skills and confidence.[52] These practical examples demonstrate that the application of AI in health management and medical training is effectively improving the quality and accessibility of medical services.

Popularizing health education: Utilizing AI technology to develop health education applications, elderly individuals can be educated about chronic diseases through voice and video, enhancing their health awareness and self-management capabilities. AI can push customized health information and preventive measures based on the health status and preferences of the elderly. For instance, the AI-powered chatbot "Ada" provides personalized health information and education by engaging users in a conversational manner, answering their health-related queries, and offering guidance on various health conditions.[53] Similarly, the "Babylon Health" app leverages AI to offer users interactive health education modules, helping them to understand their health risks and adopt healthier lifestyles.[54] These applications demonstrate how AI can be employed to disseminate health knowledge effectively and promote proactive health management among the elderly population.

Optimizing drug management: Smart pillboxes equipped with AI functions can remind the elderly to take their medication on time, record medication usage, and share information with doctors through network connectivity to ensure medication safety. AI systems can analyze patients' medication history to predict drug interactions and avoid or reduce adverse reactions. For instance, the "PillDrill"smart pillbox uses computer vision and AI to identify pills, track medication adherence, and even notify caregivers or doctors if a dose is missed.[55] Another example is the "Popit" smart pill bottle cap, which replaces the original cap of a medication bottle and uses AI to track when the bottle is opened, providing insights into medication-taking behavior.[56] Moreover, AI-powered platforms like "Talg" analyze electronic health records to identify potential drug interactions and suggest safer alternatives, helping clinicians make more informed prescribing decisions.[57] These examples demonstrate how AI-enabled devices and systems are revolutionizing medication management, improving adherence, and reducing the risk of adverse drug events, particularly among the elderly population.

Enhancing psychological support: Through AI-powered psychological counseling robots, emotional support and psychological guidance can be provided to the elderly, helping them alleviate the psychological stress caused by chronic illnesses. AI technology can monitor changes in the elderly's emotions, promptly identifying and intervening in potential psychological issues. For example, the AI-powered chatbot "Woebot" uses cognitive-behavioral therapy (CBT) principles to provide on-demand chat-based mental health support.[58] It can help users manage mood, reduce anxiety, and track their mental health progress over time. Another example is "Paro", a therapeutic robot modeled after a baby harp seal, which provides comfort and emotional support through gentle movements and sounds, particularly beneficial for individuals with dementia or Alzheimer's disease.[59] These AI-powered tools offer accessible and engaging forms of psychological support, complementing traditional therapy and providing continuous care.

Improving medical insurance efficiency and accuracy: AI insurance consultants can assist the elderly in better understanding insurance policies, selecting appropriate insurance products, and enhancing the precision of insurance coverage. AI-driven automated claims processes can streamline insurance reimbursement procedures, alleviating the financial burden on the elderly. Artificial Intelligence (AI) has significantly improved the efficiency of medical insurance reimbursement, optimized processes, and reduced fund risks. For instance, in Lvliang City, Shanxi Province, China, a medical AI engine has enabled 100% inspection of medical insurance claims, effectively reducing irregularities and decreasing the amount of funds lost to these irregularities by 30%.[60] The "Smart Assistant" of Shenzhen City's Medical Insurance in China provides 24-hour consultation services, simplifying the reimbursement process and enhancing user experience through an integrated settlement platform.[61] Additionally, AI engines can conduct full-process intelligent audits of medical behaviors, promptly detect and prevent irregularities, thus ensuring the sustainability of medical insurance funds.

Strengthening family support: Smart home devices and social robots demonstrate significant potential in health monitoring and companionship for older adults, though cultural adaptation remains critical - as evidenced by Japan's pioneering robotic nursing programs. Therapeutic robots like PARO seal robots, deployed in 68% of Japanese nursing homes (MHLW, 2023), have achieved a 23% reduction in caregiver workload (JART, 2022) and 17% improvement in dementia patients' social engagement, while physical assistants such as the Robear lifting robot reduce musculoskeletal injuries by 40%.[62,63]

In summary, the application of AI is expected to improve the current situation of Geriatric Chronic Disease Management at multiple levels, providing more comprehensive and personalized health services for the elderly.

Challenges with AI Technologies in Geriatric Chronic Disease Management

While Demonstrating Significant Potential, These Technologies Face Adoption Challenges Including

Data scarcity: This is a key challenge for the application of artificial intelligence in the medical field. High-quality, labeled medical data, especially for rare diseases or specific populations (such as the elderly or certain racial groups), is often limited. This scarcity of data seriously restricts the training and performance of AI models, leading to poor performance in specific populations or rare diseases, making it difficult to develop diagnostic and treatment plans with broad applicability and high accuracy.[64] To address this issue, data augmentation techniques such as data augmentation, transfer learning, and synthetic data generation can be used to expand the dataset, but it is also necessary to recognize the limitations of these techniques.[65] In addition, promoting cross-institutional data sharing and collaboration is crucial, but this involves considerations of ethical and privacy issues. Federated learning, as a privacy-preserving data sharing and model training method, is attracting widespread attention. It allows models to be trained collectively using data from different institutions without sharing the original data, thereby alleviating the problem of data scarcity while protecting patient privacy.[66]

Model generalization: This is a significant challenge in the application of AI in healthcare. The issue lies in the limited ability of AI models to generalize across different populations, medical institutions, or data distributions. The generalization ability of a model is crucial for ensuring the reliability and effectiveness of AI tools in real-world medical settings.[67] To address this challenge, it is essential to train models using diverse datasets to enhance their robustness. Techniques such as domain adaptation and domain generalization can be employed to improve the model's adaptability across various environments.[68] Additionally, implementing continuous learning and model update mechanisms is vital to accommodate changes in data distribution over time, ensuring that AI models remain accurate and relevant in dynamic healthcare settings.[69]

Clinician adoption: The adoption of AI tools by clinicians poses a significant challenge, as they may be skeptical of their accuracy, reliability, and potential impact on the doctor-patient relationship. In-depth analysis indicates that trust and acceptance are crucial factors influenced by explainability, transparency, and performance. Training and education for clinicians to enhance their AI literacy are vital. To address this, explainable Artificial Intelligence (XAI) technologies can be employed to improve transparency and explainability, elucidating the basis for model decisions to clinicians. XAI technologies are garnering increasing attention in the medical application of AI, as they help reveal the decision-making process of models, enabling medical professionals and patients to understand model behavior. XAI technologies include Local Interpretable Model-agnostic Explanations (LIME), Anchors, and SHapley Additive explanations (SHAP) values, which can provide detailed explanations of model decisions.[70,71] Furthermore, the importance of user experience and interface design should not be overlooked. User-friendly and intuitive AI tool interfaces need to be designed to facilitate their seamless integration into clinical workflows. Clinical engagement and collaboration are paramount, ensuring clinicians are actively involved in the development and evaluation of AI tools. Clear guidelines and frameworks need to be established to address issues of responsibility.[72–74] Finally, presenting data from surveys and interviews conducted with clinicians can provide valuable insights into their views on AI, highlighting their concerns and expectations, which is crucial for fostering broader acceptance and successful implementation of AI in healthcare.[75–77]

Alignment of AI decision-making with clinical guidelines: The decisions of artificial intelligence models need to be aligned with clinical guidelines and medical expertise. To achieve this, the development and training of the model need to use data that comply with clinical guidelines, and the model needs to be continuously evaluated and adjusted during the application process.[78] In addition, feedback and participation from healthcare professionals are crucial to ensuring the alignment of AI decisions with clinical guidelines.[79] By combining the powerful computational capabilities of artificial intelligence with the expertise of healthcare professionals, the effectiveness and reliability of artificial intelligence models in the medical field can be ensured.

Privacy and Security Issues: Health data of the elderly contains sensitive information that requires strict privacy protection. HIPAA, the Health Insurance Portability and Accountability Act, is a key regulation in the US healthcare industry, aimed at protecting patients' Protected Health Information (PHI). Its core rules include the Privacy Rule, which restricts the use and disclosure of PHI, requiring patient authorization or specific conditions; the Security Rule, which mandates technical, physical, and administrative safeguards to protect electronic PHI (ePHI); and the Breach Notification Rule, which requires timely notification of affected individuals and entities in the event of a data breach[80.] GDPR, the General Data Protection Regulation, is a data protection law applicable across the EU, governing the processing of personal data, including health data. Its core requirements include ensuring data security, empowering individuals with rights over their data (such as access, rectification, and erasure), and mandating data breach notifications within 72 hours.[81] Designing AI solutions in healthcare that comply with regulations like HIPAA and GDPR requires a multi-faceted approach. Core principles include data minimization, anonymization, encryption, and strict access controls to protect sensitive patient information. Implementing technologies such as federated learning and differential privacy can ensure AI models handle data responsibly.[82] Organizations must also conduct regular compliance reviews, employee training, and data protection impact assessments. Additionally, having a robust data breach response plan and contractual agreements with third-party providers are crucial. By integrating these technical, managerial, and legal measures, AI solutions can effectively safeguard patient data while adhering to regulatory requirements.[83]

Integration with existing healthcare systems: This is crucial for the successful deployment of AI tools. However, integrating AI tools into existing healthcare workflows and systems presents technical and operational challenges. These challenges include differences in data formats and communication protocols between various healthcare systems, which hinder interoperability.[84] Furthermore, AI tools need to be adapted to existing clinical workflows, which may require necessary adjustments to avoid disrupting medical efficiency. To address these issues, it is crucial to establish data exchange standards and develop common interfaces to ensure seamless information sharing between different systems.[85] Integration with Electronic Health Record (EHR) systems is also vital, requiring exploration of best practices and addressing related challenges, such as data security and privacy protection.[86] By adopting a phased approach through pilot projects and iterative development, the integration of AI tools with existing healthcare systems can be gradually achieved and continuously improved through practical application.

User Acceptance: The elderly often struggle to accept AI-powered health tools due to a lack of tech familiarity, declining cognitive abilities, and a preference for traditional doctor-patient interactions. They may fear data breaches and mistrust AI diagnoses, for instance, questioning AI's accuracy in diabetic retinopathy screening. The reduced human contact in AI-managed care can also lead to feelings of isolation.[87] To improve acceptance, we must simplify interfaces, provide community-based training, ensure data security, promote AI's benefits while emphasizing the continued role of human doctors, and encourage family support, particularly from their children, in learning these new tools.[87]

Ethical and Legal Issues: The integration of AI into medical decision-making, particularly in geriatric chronic disease management, raises significant ethical and legal concerns that demand clear guidance. Responsibility attribution becomes a critical issue when, for example, an AI system recommends a medication change that leads to an adverse reaction. Determining whether the responsibility lies with the developers, the healthcare provider who implemented the system, or even the AI itself, is a complex question. Similarly, a lack of transparency in how AI algorithms arrive at diagnostic or treatment suggestions can erode trust and hinder informed consent, as seen when an AI tool flags a patient for a specific risk without revealing the underlying reasoning. Furthermore, fairness is compromised if AI models, trained on biased datasets, disproportionately misdiagnose or undertreat certain demographic groups, such as minority populations within the elderly. These challenges underscore the need for robust ethical frameworks, transparent and explainable AI systems, and diverse, representative training data to ensure equitable and responsible use of AI in managing chronic diseases in the elderly, ultimately safeguarding their well-being and rights.[88,89]

To overcome these shortcomings, interdisciplinary collaboration is needed, including technology developers, medical professionals, policymakers, and patient representatives, to jointly promote the rational and effective application of AI in the Geriatric Chronic Disease Management.

Summary

In summary, AI is profoundly impacting geriatric chronic disease management of aging societies. It can optimize resource allocation, control medical costs, enhance the accessibility of medical services, and improve the elderly's medical experience through technologies like telemedicine. However, issues such as data privacy, algorithmic bias, ethical responsibility, and the changing roles of healthcare workers also require attention. Policymakers need to promote the development of AI technology while formulating relevant regulations and ethical guidelines to ensure data security, fairness, and transparency, and support the professional development of healthcare workers. The ultimate goal is to enable the elderly to enjoy high-quality, personalized, and equitable medical care.

In the future, research on AI in geriatric healthcare will focus on the following aspects: realizing personalized medicine by leveraging big data and machine learning to tailor health management plans for the elderly, and conducting real-time health monitoring and early warning through intelligent wearable devices; promoting intelligent services for the elderly, simplifying medical processes through technologies such as voice interaction and virtual assistants, and expanding the coverage of AI-assisted old-age rehabilitation services in combination with medical insurance policies; and conducting interdisciplinary collaborative research, which requires the joint efforts of fields such as medicine, computer science, and sociology, and learning from international advanced experiences to jointly address the challenges brought by an aging society.

Disclosure

The authors report no conflicts of interest in this work.

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