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Letter to Editor

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Artificial Intelligence in Older Adults' Health

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Dear Editor,

With the growing older adult population globally, there is an increasing need to find innovative solutions to address their health needs. Artificial Intelligence (AI) has emerged as a beneficial tool for diagnosing and predicting health issues across various medical fields.^{1,2} AI can enhance personalized healthcare for older adults, significantly improving their overall quality of life and well-being.³

This study aimed to provide a concise overview of AI techniques, applications, evaluation metrics, ethical considerations, biases, and associated challenges associated with AI models in healthcare.

AI Techniques and Their Real-World Applications in Older Adults' Healthcare

Support vector machines (SVMs) and k-nearest neighbors are commonly used for tasks such as classifying falls among older adults or identifying individuals at risk of diseases, while random forest (RF) excels in analyzing clinical data and medication histories due to their ability to manage missing values.⁴⁻⁷ Additionally, convolutional neural networks demonstrated high accuracy in medical imaging, particularly in detecting early signs of diseases such as Alzheimer's. Recurrent neural networks, on the other hand, are used to analyze time-series data such as electrocardiograms and cognitive monitoring, although they require more computational resources.^{8,9} Lastly, artificial neural networks and deep learning are utilized to predict imaging outcomes and drug interactions.⁹

Machine learning (ML) algorithms such as decision trees, RF, and SVMs can predict when diseases might start or worsen, facilitating early treatment and personalized care plans.10 For example, hospitals in the USA have integrated AI solutions like SVM and RF algorithms to identify cardiovascular diseases in older adults.¹¹ In addition, in mental health, AI has been used to monitor

conditions such as dementia and depression, offering timely interventions and supporting personalized care.¹²⁻ ¹⁴ It plays a crucial role in improving mental health by providing tailored nutrition and diet plans, optimizing rehabilitation and physical therapy programs, and reducing the risk of adverse drug reactions through improved medication management.¹⁵⁻¹⁷ In addition, AIpowered personalized medicine analyzes patient records to suggest tailored treatment options, thereby enhancing outcomes in older adult care.¹⁸

Furthermore, natural language processing techniques can help manage medications by analyzing and understanding patient records, ensuring that patients take their medications correctly and avoid harmful drug interactions. Furthermore, reinforcement learning algorithms can optimize rehabilitation and physical therapy programs by adapting to the specific needs and progress of older adults.19,20

Moreover, AI approaches can be applied in pain management for various conditions in older adults, and their remote monitoring can also offer a cost-effective alternative to traditional visits, improving care and reducing healthcare costs, particularly for chronic diseases in older adults.21,22

Evaluation Metrics for AI Models in Healthcare

Evaluating AI models in older adults' healthcare involves metrics such as accuracy, precision, recall, F1-score, and area under the curve (AUC)-receiver operating characteristics (ROC). Accuracy assesses correct predictions, while precision and recall focus on positive predictability and true positives, respectively. The F1 score provides a balance between precision and recall, which is crucial in disease diagnosis, and AUC-ROC helps distinguish classes, making it valuable for imbalanced datasets.23-26 These metrics are essential for ensuring

timely and reliable predictions, which are critical in older adults' care.

Ethical Considerations, Bias, and Challenges

Challenges related to ethics, transparency, and data privacy persist in the application of AI. A key ethical challenge with AI in healthcare is the lack of transparency and interpretability, which makes it difficult for healthcare providers to understand the decision-making processes. Biases in AI models due to unbalanced training data can also affect aging populations, leading to less effective care. Addressing these issues requires age diversity in data collection, routine audits, and overcoming limitations (e.g., data privacy concerns and the digital divide). $27-33$ Greater trust in AI systems is associated with increased adherence to health recommendations, indicating that cultivating trust can improve health outcomes.^{34,35}

The use of ML and AI methods in epidemiological studies, as opposed to traditional methods, has demonstrated their capacity to manage large complex datasets while detecting subtle patterns and associations. This capability is crucial given the extensive and multifaceted nature of health data.36 AI facilitates more efficient public health research and interventions, especially for older individuals.

Integrating AI and ML into older adults' healthcare is essential for creating a more efficient and compassionate system. It is suggested that policymakers, healthcare providers, researchers, and editors collaborate and invest in these technologies for a healthier future for older adults.37,38

Author contributions

Conceptualization: Nazanin Masoudi. **Methodology:** Ehsan Sarbazi, Nazanin Masoudi. **Supervision:** Ehsan Sarbazi. **Writing–review & editing:** Ehsan Sarbazi, Nazanin Masoudi.

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Conflict of interests

The authors declare that they have no conflict of interests.

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