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Artificial Intelligence-Based Diagnosis and Personalized Treatment Strategies for Alzheimer's Disease: Current Tools, Limitations, and Future Prospects

Shaikh Ainul Shafeeque¹, Jaswandi Mehetre², Vimal Kumar³

School of Pharmacy, ITM SLS Baroda University, Vadodara, India¹⁻³

ABSTRACT: Alzheimer's disease (AD) is a progressive neurodegenerative disorder characterized by cognitive decline, memory impairment, and functional deterioration. Early and accurate diagnosis, along with personalized treatment strategies, remains a major clinical challenge due to heterogeneous symptoms, overlapping pathologies, and subtle preclinical onset. Conventional diagnostic methods such as cognitive assessments, neuroimaging (MRI, PET), and cerebrospinal fluid biomarker analysis are limited by subjectivity, invasiveness, high costs, and low sensitivity, often resulting in delayed diagnosis and suboptimal patient care. Artificial Intelligence (AI) has emerged as a transformative tool for improving AD diagnosis and treatment. Current AI-based tools used by neurologists include IBM Watson Health, NeuroQuant, Qure.ai, and Corti.ai, which assist in neuroimaging analysis, pattern recognition, risk prediction, and clinical decision support. AI systems can detect subtle structural and functional brain changes, predict disease progression, and enable early identification of at-risk individuals. In treatment planning, AI supports personalized therapeutic strategies by integrating patient-specific clinical data, biomarker profiles, and lifestyle factors, while AI-driven remote monitoring tools enhance adherence and continuous care. Despite these advances, several AI approaches remain underutilized in clinical practice. These include causal AI for understanding disease mechanisms and treatment effects, federated learning for secure multi-institutional collaboration, neuro-symbolic AI for integrating clinical knowledge with data-driven insights, explainable AI (XAI) to enhance clinician trust, and multimodal foundation models capable of reasoning across diverse datasets. Challenges such as interpretability, regulatory compliance, and workflow integration limit broader adoption. Future integration of these AI methodologies could revolutionize AD care by overcoming current diagnostic limitations, enabling precision treatment, improving early detection, optimizing therapy strategies, and enhancing patient outcomes. The continued development of interpretable, collaborative, and clinically compatible AI systems is expected to shape the future of Alzheimer's diagnosis and management.

KEYWORDS: Alzheimer's disease, artificial intelligence, neuroimaging, early diagnosis, personalized treatment

I. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative disorder most commonly characterized by early memory impairment and cognitive decline, which may ultimately affect behaviour, language, visuospatial orientation, and motor function. AD represents the most prevalent cause of dementia worldwide [1,2]. It is estimated that over 47 million individuals globally are affected by dementia, with annual healthcare and societal costs exceeding USD 1 trillion as of 2018. AD accounts for approximately 60–80% of all dementia cases, although fewer than half of these are considered "pure" AD, with mixed dementia pathologies being common [2].

Amyloid- β (A β) accumulation leads to the formation of extracellular amyloid plaques within the brain parenchyma and cerebral vasculature, a condition known as cerebral amyloid angiopathy. Neurofibrillary tangles (NFTs), composed of paired helical filaments of hyperphosphorylated tau protein, are associated with neuronal and synaptic loss and represent a hallmark pathological feature of AD. Traditionally, AD has been conceptualized as a disorder involving progressive neuronal and synaptic degeneration occurring in specific anatomical regions, resulting in distinct clinical phenotypes [1,3]. Animal models, such as vervets, exhibit early amyloid deposition without corresponding tau

pathology or widespread neurodegeneration, limiting their translational relevance to human AD. Nevertheless, these models remain valuable for studying early amyloid-related behavioural and biomarker changes [4].

Current AD treatment strategies have predominantly relied on single-target pharmacological approaches, which represent a major limitation given the multifactorial nature of the disease. This has prompted a paradigm shift toward multi-target-directed ligand (MTDL) discovery. Evidence suggests that therapies targeting a single pathological pathway have failed to produce meaningful clinical improvement or disease modification. Moreover, responses to FDA-approved therapies vary considerably across patients. For example, the cognitive benefits associated with donepezil are typically modest and transient [5]. While existing pharmacotherapies may provide temporary symptomatic relief or modestly slow cognitive decline, they do not halt disease progression. Single-target strategies are frequently associated with limited efficacy and adverse effects such as dizziness, nausea, and diarrhoea, which are particularly challenging for elderly patients. These limitations underscore the urgent need for therapeutic strategies that address multiple disease pathways simultaneously [5].

Many anticholinergic and amyloid-targeting agents have demonstrated only marginal and short-lived clinical benefits, with limited impact on neurodegeneration. Despite extensive pharmaceutical investment, most drug candidates targeting amyloid hypothesis or dopamine-related mechanisms have failed to progress beyond early research stages [5]. Drug development for AD remains inherently complex, with challenges spanning target identification, clinical trial design, regulatory approval, and real-world implementation [5].

II. RATIONALE FOR AI-DRIVEN SOLUTIONS IN AD CARE

Large-scale international datasets, such as the Alzheimer's Disease Neuroimaging Initiative (ADNI), provide extensive genetic, clinical, and neuroimaging data from cognitively normal individuals, patients with mild cognitive impairment (MCI), and those with AD. Artificial intelligence (AI) techniques can leverage these datasets to identify definitive genetic markers (DGMs), as well as concurrent cognitive, linguistic, psychological, and behavioural indicators relevant to early diagnosis and treatment [6].

First, AI-driven causal models can be developed to identify upstream DGMs associated with late-onset Alzheimer's disease (LOAD) using ADNI data. Second, longitudinal validation in specific populations—such as Han Chinese cohorts—can determine whether individuals with MCI carrying these DGMs have a higher risk of progression to LOAD compared with cognitively normal controls. Third, AI can identify concurrent cognitive, linguistic, and behavioural markers in genetically at-risk individuals [6].

In the future, integrated AI-driven causal frameworks combining genetic, clinical, linguistic, cognitive, and behavioural data in a longitudinal manner may accelerate early disease detection and facilitate drug repurposing efforts, enabling the identification of multi-drug combinations from existing FDA-approved agents [6].

III. CONVENTIONAL DIAGNOSTIC AND THERAPEUTIC CHALLENGES IN AD COGNITIVE ASSESSMENTS, NEUROIMAGING, AND BIOMARKER LIMITATIONS

A central goal of Alzheimer's disease research is the identification of reliable biomarkers that can detect pathological changes during the preclinical stage, enabling early diagnosis and timely intervention. Biomarkers represent quantifiable indicators of biological processes associated with AD and are often used as surrogate measures of disease progression. Over the past decade, substantial progress has been made in developing neuroimaging-based biomarkers using modalities such as magnetic resonance imaging (MRI), positron emission tomography (PET), and functional imaging techniques.

Neuroimaging approaches provide valuable insights into multiple pathophysiological mechanisms, including structural brain changes such as cortical thinning and regional volume loss, functional alterations such as disrupted network connectivity and functional hyperactivity, white matter degeneration assessed through diffusion tensor imaging, and pathological protein aggregation visualized using amyloid and tau PET imaging. Despite these advances, each modality has inherent limitations related to sensitivity, specificity, cost, and accessibility. Consequently, single-modality biomarkers often fail to capture the full complexity of disease progression. Emerging evidence suggests that combining

multiple imaging modalities into composite biomarkers may enhance diagnostic accuracy and provide more robust outcome measures for proof-of-concept clinical trials evaluating disease-modifying therapies [7]

VI. DISEASE HETEROGENEITY AND DELAYED DIAGNOSIS

Alzheimer's disease exhibits substantial heterogeneity in terms of clinical presentation, progression rate, and underlying pathology. This variability poses significant challenges for both diagnosis and therapeutic evaluation. Studies using data from the Alzheimer's Disease Neuroimaging Initiative have demonstrated that unaccounted heterogeneity in disease progression can substantially influence cognitive outcome measures and obscure treatment effects in clinical trials.

Failure to account for individual variability may result in reduced statistical power and inconsistent effect sizes between treatment and placebo groups, particularly in trials targeting prodromal and mild AD stages. Known modifiers of disease progression include age, sex, educational attainment, cerebrospinal fluid tau levels, and apolipoprotein E (APOE) $\epsilon 4$ carrier status. Stratification of patients based on these risk factors has been shown to reduce outcome variability and improve the detection of treatment effects. These findings underscore the importance of personalised risk profiling and early stratification to minimise diagnostic delay and enhance clinical trial efficiency [8].

VII. GAPS IN PERSONALIZED TREATMENT STRATEGIES

Personalised care in Alzheimer's disease aims to move beyond standardised treatment approaches by adopting precision medicine principles that account for individual biological, genetic, lifestyle, and environmental factors. Precision medicine seeks to optimise therapeutic efficacy while minimising adverse effects by tailoring interventions to the unique characteristics of each patient.

Effective personalisation requires accurate and early diagnosis, integration of biomarker and phenotypic data, and consideration of psychosocial factors that influence disease experience and treatment adherence. Person-centred care models emphasise patient autonomy, informed decision-making, and continuity of care, while also recognising the essential role of family members, caregivers, and care partners. Despite its potential, personalised treatment in AD remains underdeveloped due to limitations in predictive tools, incomplete biological understanding, and insufficient integration of patient-specific data into clinical decision-making frameworks [9].

VIII. CURRENT AI-BASED TOOLS IN ALZHEIMER'S DISEASE AI APPLICATIONS IN NEUROIMAGING (MRI, PET) AND BIOMARKER ANALYSIS

Artificial intelligence, particularly machine learning and deep learning techniques, has emerged as a powerful approach in neurodegenerative disease research, offering data-driven solutions for early diagnosis, prediction of cognitive decline, and identification of disease-related biomarkers. AI models are increasingly applied to the analysis of multimodal neuroimaging data, including magnetic resonance imaging (MRI), positron emission tomography (PET), and electroencephalography (EEG), to enhance diagnostic precision and prognostic accuracy.

Advanced deep learning architectures, such as convolutional neural networks and transformer-based models, enable the detection of subtle structural and functional brain alterations that may precede overt clinical symptoms. These models can identify region-specific atrophy patterns, altered connectivity networks, and early pathological protein deposition with higher sensitivity than conventional analytic methods. Given that Alzheimer's disease affects more than 55 million individuals worldwide and is projected to exceed 150 million cases by 2050, AI-driven neuroimaging analysis represents a critical tool for addressing the growing global burden of dementia [10].

In addition to neuroimaging, AI techniques facilitate the integration of complex biological data, allowing for improved disease staging and progression modelling. By analysing longitudinal datasets, AI systems can predict disease trajectories and support risk stratification, contributing to more informed clinical decision-making. Collectively, these advances highlight a paradigm shift in neurology toward data-driven, precision-based diagnostic approaches [10].

IX. CLINICAL DECISION SUPPORT SYSTEMS

Clinical decision support systems (CDSS) are computer-based tools designed to assist healthcare professionals by analyzing electronically derived patient data, including clinical symptoms, laboratory results, imaging findings, genetic information, and neuropsychological assessments. In the context of Alzheimer's disease, CDSS platforms support diagnostic evaluation, disease staging, and treatment planning, thereby reducing diagnostic uncertainty and enhancing clinical efficiency [11].

AI-enabled CDSS platforms such as IBM Watson Health, NeuroQuant, and Qure.ai analyze structured and unstructured clinical data to generate evidence-based recommendations and risk assessments. These systems can support less experienced clinicians, promote guideline-adherent care, and facilitate personalized treatment planning. Integration of CDSS into electronic health record systems enables real-time, point-of-care decision-making, further enhancing their clinical utility [12].

Corti is an AI-powered system used by emergency dispatch centers to analyze real-time audio from emergency calls. It detects signs of cardiac arrest or stroke by recognizing patterns in the caller's voice, breathing sounds, and background noise. The system provides instant feedback to dispatchers, prompting them to initiate life-saving measures like CPR instructions. This technology enhances the speed and accuracy of emergency responses and can outperform human recognition in time-critical scenarios [12].

Qure. AI: is an tools assist radiologists by using deep learning algorithms to analyze a wide range of medical images such as X-rays, CT scans, MRI, and PET scans. They can identify subtle signs of critical conditions like intracranial hemorrhage, pulmonary embolism, cancerous lesions, and spinal fractures. Some platforms offer real-time triaging—flagging life-threatening issues first for immediate review. Integration with PACS (Picture Archiving and Communication Systems) and EHRs helps streamline radiology workflows, improve turnaround time, and reduce missed diagnoses, especially in high-volume settings [12].

X. AI FOR EARLY DETECTION, RISK PREDICTION, AND DISEASE PROGRESSION

Beyond imaging-based diagnostics, AI has demonstrated significant potential in identifying early behavioural and motor biomarkers of neurodegenerative disease. Changes in speech and language processing often occur during the preclinical stages of Alzheimer's disease and can serve as sensitive indicators of cognitive impairment. AI-based speech analysis has identified features such as increased hesitation, reduced lexical diversity, and simplified sentence structure, which are associated with early semantic and executive dysfunction.

Machine learning models trained on large speech datasets can differentiate pathological speech patterns from those associated with normal ageing, enabling remote cognitive screening through voice recordings obtained via clinical interviews or digital applications. In parallel, gait abnormalities, including reduced walking speed, shortened step length, and increased stride variability, have been recognized as early markers of neurodegeneration. Wearable sensors equipped with accelerometers and gyroscopes provide continuous movement data that can be analyzed using AI algorithms to detect subtle motor changes.

Studies have demonstrated that deep learning models analyzing gait patterns can identify individuals at risk of neurodegenerative disorders several years before clinical diagnosis. The integration of speech and gait analysis into AI-driven monitoring frameworks offers a non-invasive, cost-effective approach to early detection and longitudinal disease monitoring, reducing reliance on expensive and invasive diagnostic procedures [10].

XI. AI-DRIVEN PERSONALIZED TREATMENT STRATEGIES**Integration of multimodal patient data for precision medicine**

The integration of multimodal data has become increasingly important in understanding and managing complex neuropsychiatric disorders such as Alzheimer's disease. Neuroimaging techniques provide critical insights into brain structure, function, perfusion, and metabolism; however, translating these findings into individual-level clinical decision-making remains challenging. Traditional statistical approaches, while effective at group-level analysis, often lack the capacity to generate accurate predictions at the individual patient level.

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Artificial intelligence, particularly machine learning and deep learning methods, is well suited to modelling complex interactions among high-dimensional datasets. By integrating multimodal neuroimaging data with genetic, clinical, and behavioural information, AI models can extract complementary features across modalities, thereby improving diagnostic accuracy and prognostic performance. Large-scale neuroimaging datasets and advances in multimodal AI frameworks present an opportunity to develop next-generation biomarkers capable of supporting early detection and personalised therapeutic strategies.

Despite their promise, multimodal AI approaches remain underutilised in clinical practice, with most existing applications relying on unimodal data sources. A comprehensive integration of structural, functional, and molecular imaging modalities is essential for a holistic understanding of disease pathogenesis and for enabling timely, targeted interventions [13].

XII. AI-ASSISTED THERAPEUTIC PLANNING AND OUTCOME PREDICTION

Cognitive decline associated with Alzheimer's disease can significantly impair a patient's ability to understand, remember, and adhere to complex medical regimens. Consequently, personalised treatment strategies must extend beyond pharmacological interventions to include simplified medication schedules, caregiver involvement, and supportive digital tools such as reminders and electronic pill organisers.

Personalised medicine aims to overcome the limitations of standardised care by tailoring therapeutic strategies to an individual's genetic, clinical, and psychosocial profile. Pharmacogenomics plays a key role in this approach by enabling clinicians to select and dose medications based on genetic variants that influence drug metabolism and transport. For example, variations in cytochrome P450 enzymes can significantly affect treatment response and tolerability, and identifying these variants can guide more effective and safer prescribing decisions.

The integration of real-world data, electronic health records, and AI-enabled clinical decision support tools further enhances patient-specific care planning. By incorporating comorbidities, historical treatment responses, and longitudinal health data, AI systems can support adaptive therapeutic strategies and improve clinical outcomes [14].

XIII. REMOTE MONITORING, DIGITAL BIOMARKERS, AND TREATMENT ADHERENCE

Remote monitoring technologies using wearable and portable sensors have transformed healthcare by enabling continuous, real-time assessment of physiological and behavioural parameters. Devices such as smartwatches, fitness trackers, and portable health monitors can collect data on physical activity, gait, sleep patterns, heart rate, and falls, providing valuable insights into disease progression and functional status in patients with Alzheimer's disease.

Incorporation of environmental sensors within the home setting allows for monitoring of movement patterns, temperature, and safety-related events, such as wandering or falls. AI-driven analytics applied to these data streams enable early detection of clinically significant changes and facilitate timely interventions. Remote monitoring frameworks also offer significant advantages for long-term disease management by supporting treatment adherence, reducing caregiver burden, and enabling continuous data collection for research purposes [15].

Digital biomarkers derived from online and remote cognitive assessments further expand the potential of non-invasive disease monitoring. Web-based cognitive testing platforms enable large-scale data collection and increased participation from underrepresented populations. Validation of these tools against traditional, laboratory-based assessments is essential to ensure reliability and clinical relevance. Once validated, digital biomarkers can complement conventional diagnostic approaches and enhance longitudinal tracking of cognitive decline [16].

XIV. EMERGING AND UNDERUTILIZED AI APPROACHES

Causal AI for disease mechanism and treatment-effect modelling

Advances in computational power have accelerated the development of highly accurate artificial intelligence models for disease classification and prediction. However, many deep learning systems function as "black boxes," limiting their interpretability and hindering clinical adoption. In the context of Alzheimer's disease, understanding the causal

relationships between biological mechanisms, clinical features, and treatment responses is critical for effective intervention.

Causal AI aims to move beyond predictive correlations by modelling cause–effect relationships underlying disease progression and therapeutic outcomes. By integrating causal inference techniques with longitudinal clinical and biological data, these models can provide insights into disease mechanisms, identify modifiable risk factors, and support treatment-effect estimation. The adoption of causal AI approaches may enable more reliable predictions of long-term outcomes and improve confidence in AI-assisted clinical decision-making [17].

XV. FEDERATED LEARNING FOR PRIVACY-PRESERVING MULTI-CENTER COLLABORATION

Machine learning applications in Alzheimer’s disease research are often limited by restricted access to large, diverse datasets due to ethical and legal constraints on patient data sharing. Although healthcare institutions possess substantial volumes of relevant data, privacy regulations frequently prevent centralised data aggregation.

Federated learning offers a promising solution by enabling model training across multiple institutions without transferring raw patient data. Instead, models are trained locally, and only model parameters are shared and aggregated. This approach preserves data privacy while allowing the development of robust, generalisable models. Recent studies applying federated learning to structural MRI data for Alzheimer’s disease detection have demonstrated its feasibility and effectiveness, even in the presence of demographic and diagnostic heterogeneity across participating sites [18].

XVI. NEURO-SYMBOLIC AI FOR COMBINING CLINICAL EXPERTISE WITH DATA-DRIVEN MODELS

Neuro-symbolic artificial intelligence represents a hybrid approach that combines the pattern recognition capabilities of deep learning with the logical reasoning strengths of symbolic AI. While neural networks excel at processing high-dimensional biomedical data, they often lack transparency. Conversely, symbolic systems provide explicit reasoning and interpretability but struggle with complex, unstructured data.

By integrating these complementary paradigms, neuro-symbolic AI frameworks offer improved interpretability, robustness, and clinical relevance. In Alzheimer’s disease research, such systems have the potential to incorporate clinical guidelines, expert knowledge, and disease ontologies alongside data-driven insights, thereby supporting more transparent and clinically meaningful predictions. Ongoing research is focused on refining these hybrid architectures to better capture disease trajectories and individual variability [19].

XVII. EXPLAINABLE AI (XAI) FOR TRANSPARENCY AND CLINICIAN TRUST

Explainable artificial intelligence plays a crucial role in bridging the gap between AI model performance and clinical trust. In healthcare settings, clinicians must understand the rationale underlying algorithmic predictions to ensure accountability, ethical compliance, and patient safety.

Recent analyses have highlighted the importance of combining technical explainability methods with human-centred design principles and regulatory considerations. Explainable AI frameworks enable clinicians to interpret model outputs, assess their reliability, and integrate AI insights into clinical reasoning. By enhancing transparency and accountability, explainable AI supports responsible adoption of AI technologies in Alzheimer’s disease care and promotes long-term sustainability of AI-driven healthcare solutions [20].

XVIII. MULTIMODAL FOUNDATION MODELS FOR COMPREHENSIVE REASONING

Effective management of Alzheimer’s disease increasingly relies on the integration of diverse data sources, including neuroimaging, clinical assessments, speech analysis, and wearable sensor data. While traditional methods often rely on fragmented and modality-specific analyses, multimodal foundation models aim to unify heterogeneous data streams within a single analytical framework.

These models are designed to learn shared representations across modalities, enabling comprehensive reasoning and improved generalisability. Emerging “AI-first” integration strategies emphasise data harmonisation and model

architectures optimised for multimodal fusion. Such approaches have the potential to overcome limitations of conventional preprocessing techniques and support scalable, longitudinal disease modelling. Despite their promise, multimodal foundation models remain in the early stages of clinical translation and require further validation [21].

XIX. CHALLENGES AND LIMITATIONS INTERPRETABILITY AND TRUSTWORTHINESS OF AI MODELS

One of the principal challenges in applying artificial intelligence to Alzheimer's disease diagnosis and management is the limited interpretability of many high-performing models. Deep learning systems often require large datasets to generate reliable and robust predictions; however, medical datasets are frequently constrained by small sample sizes, missing data, and population biases. These limitations can reduce model generalisability and hinder the reliability of explainable outputs.

Explainable AI frameworks aim to provide transparency by highlighting the features or patterns influencing model predictions. Nevertheless, explanations generated by different XAI methods may vary, leading to ambiguity and potential confusion among clinicians. Furthermore, explanations are sometimes developed without sufficient clinical input, which may result in interpretations that are misaligned with established medical knowledge. The absence of validated ground-truth explanations further complicates objective assessment of model interpretability. As a result, a trade-off often exists between model accuracy and interpretability, underscoring the need for clinically guided, standardised XAI validation strategies in Alzheimer's disease research [22].

Regulatory, ethical, and data privacy concerns

AI-driven technologies for Alzheimer's disease hold significant promise for continuous, non-invasive monitoring and early detection of cognitive decline. Such approaches may reduce missed or delayed diagnoses and support timely clinical intervention and life planning. However, the collection and use of digital biomarkers raise substantial ethical and regulatory challenges.

Many digital monitoring tools are developed and operated by non-healthcare entities that may not be subject to the same regulatory standards governing clinical data. Although general data protection laws offer some safeguards, they may not adequately address the sensitivity and longitudinal nature of health-related data. Issues related to informed consent, data ownership, security, and secondary data use remain critical concerns. Ensuring compliance with healthcare-specific privacy regulations and establishing transparent governance frameworks are essential for the responsible deployment of AI technologies in Alzheimer's disease care [23].

Clinical workflow integration and real-world validation

Successful translation of AI models into clinical practice requires seamless integration into existing healthcare workflows and validation under real-world conditions. While controlled clinical trials provide evidence of efficacy, they often involve highly selected patient populations and limited follow-up durations, which may not reflect routine clinical settings.

Real-world studies enable evaluation of AI tools across diverse populations, longer disease trajectories, and varying healthcare environments. Such studies can capture delayed treatment effects, assess cost-effectiveness, and identify practical implementation challenges. Observational data collected in real-world contexts also support assessment of safety, usability, and clinical impact beyond traditional trial endpoints. Robust real-world validation is therefore critical to ensuring that AI-driven solutions deliver meaningful and generalisable benefits in Alzheimer's disease management [24].

Future Prospects and Clinical Implications

Role of advanced AI in early diagnosis and precision therapy

Artificial intelligence has increasingly been explored for its potential to support early detection and prediction of Alzheimer's disease progression. However, limited interpretability and transparency of many AI models have constrained their clinical applicability. This has led to growing interest in explainable artificial intelligence approaches that provide clear and comprehensible insights into model decision-making processes.

Explainable AI focuses on developing transparent and interpretable models capable of articulating the rationale underlying predictions. By enhancing clinician understanding and trust, XAI enables meaningful human oversight and informed decision-making. The integration of explainable frameworks with non-invasive data sources, such as speech, gait, and digital biomarkers, offers a promising pathway for improving early diagnosis while maintaining clinical accountability. Such approaches may also provide deeper insights into disease mechanisms, thereby facilitating precision therapy and improved patient stratification [25].

Potential Impact on Patient Outcomes and Healthcare Systems

Recent developments in disease-modifying therapies highlight both progress and ongoing challenges in Alzheimer's disease treatment. For example, the anti-amyloid monoclonal antibody aducanumab received accelerated approval based on its ability to reduce amyloid burden; however, its clinical benefit in slowing cognitive decline remains uncertain, and treatment is associated with notable adverse events. In addition, economic considerations, including drug pricing and reimbursement policies, significantly influence access and long-term sustainability of emerging therapies. [26].

The broader economic burden of Alzheimer's disease extends beyond direct pharmacological costs to include healthcare utilisation, long-term care, caregiver burden, and out-of-pocket expenses. AI-driven diagnostic and monitoring tools may help optimise resource allocation, reduce unnecessary interventions, and support earlier care planning, thereby potentially mitigating overall healthcare costs and improving patient quality of life techniques for causal discovery and inference to longitudinal AD data could yield crucial insights into patient-specific mechanisms of decline.[27]

XX. CONCLUSION

Artificial intelligence has demonstrated substantial potential in advancing the diagnosis and management of Alzheimer's disease. AI-based tools have improved early detection, neuroimaging analysis, biomarker interpretation, and disease progression modelling, thereby supporting more accurate clinical decision-making and personalized treatment strategies through multimodal data integration. Despite these advances, significant challenges remain. Limited external validation, reduced generalisability across diverse populations, interpretability concerns, regulatory barriers, and insufficient integration into clinical workflows continue to restrict widespread clinical adoption. Moreover, advanced AI approaches such as causal modelling, federated learning, and multimodal foundation models remain underexplored in real-world clinical settings. The successful translation of AI into Alzheimer's disease care requires the development of collaborative, interpretable, and patient-centred systems. Interdisciplinary collaboration among clinicians, researchers, data scientists, and regulatory authorities is essential to ensure ethical design, clinical relevance, and robust validation. Explainable AI plays a critical role in fostering clinician trust and supporting transparent, accountable decision-making. Patient-centred AI systems that incorporate individual clinical characteristics, continuous monitoring, and personalised interventions have the potential to improve treatment adherence, quality of life, and long-term outcomes. The integration of collaborative, interpretable, and clinically compatible AI solutions will be essential for achieving sustainable and meaningful impact in the care of individuals with Alzheimer's disease.

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