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Research Progress on Artificial Intelligence-Based Early Diagnosis and Treatment of Alzheimer's Disease

Roujia Sha[1], Weike Feng[2]

[1]College of Traditional Chinese Medicine, Shandong University of Traditional Chinese Medicine, Jinan 250355, China
[2]Department of Biochemistry, School of Medicine, Shandong University of Traditional Chinese Medicine, Jinan 250355, China

Author to whom correspondence should be addressed.

Abstract: Alzheimer's disease (AD) is one of the most common neurodegenerative diseases and continues to place a considerable burden on public health systems worldwide. Owing to its complicated pathological mechanisms, difficulties associated with early diagnosis, and the lack of treatments capable of halting disease progression, AD remains a major focus of current research. In recent years, artificial intelligence (AI) has increasingly been introduced into this field. Methods based on machine learning, deep learning, and the integration of different types of data have shown potential in several aspects of AD research and clinical care. Existing studies have explored the use of AI for identifying AD at earlier stages, analyzing neuroimaging data, estimating disease progression, supporting digital health interventions, and assisting drug development. This review summarizes recent work in these areas and focuses on several topics that have attracted particular attention, such as neuroimaging applications, biomarker discovery, cognitive and behavioral evaluation, long-term disease monitoring, and therapeutic support. At the same time, a number of issues continue to limit wider clinical adoption. Differences in data sources, insufficient generalizability of some models, and concerns regarding ethics, privacy, and data security are among the challenges most frequently discussed in the literature. Addressing these problems will be important for the future development and practical use of AI-based approaches in AD diagnosis and management.

Keywords: Alzheimer's disease; Artificial intelligence; Machine learning; Deep learning; Neuroimaging; Blood biomarkers

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1. Introduction

Alzheimer's disease (AD) is generally considered the main cause of dementia. It is a progressive disorder of the central nervous system, and the pathological picture is usually described with a few key features:

extracellular β-amyloid (Aβ) deposits, abnormal Tau phosphorylation, loss of neurons, and ongoing neuroinflammatory changes [1–2]. These features are widely known, but more recent studies suggest that the disease is not as uniform as it was once thought. In fact, there seems to be a fair amount of biological variation between patients, both in how the disease starts and how it progresses.

This has affected how diagnosis is framed. The 2018 NIA-AA research framework already moved away from diagnosing AD purely based on symptoms, and instead focused more on biological markers [1]. Later, in 2024, this idea was further extended. The AT(N) system was expanded into a broader AT1T2NISV structure, which now includes additional indicators such as astrocyte-related biomarkers (GFAP/AST) and markers linked to synaptic damage [3]. What this basically shows is a gradual shift in the field: diagnosis is becoming more biological and less symptom-based, although in practice this transition is still ongoing.

At the same time, research on inflammation has become more central than before. Microglia and innate immune pathways are no longer seen only as a reaction to neuronal damage. There is now growing evidence that they may take part in the disease process at multiple stages, not just at the endpoint [2].

Outside the laboratory context, the social burden of AD is also increasing. Population aging is one of the main reasons for this trend. In China, the situation has become more and more noticeable in recent years. The China Alzheimer's Disease Report 2024 points out that the number of patients is still increasing, which naturally puts pressure on both the healthcare system and families who provide long-term care [4]. Around the same time, the Alzheimer's Disease Prevention and Treatment Association of China issued the Chinese Expert Consensus on Multidimensional Rehabilitation Interventions for Alzheimer's Disease (2025). It basically suggests a mixed model of management, combining hospitals, community services, and family-based support [5]. The overall direction is quite clear, although how it will be implemented in different regions may still vary.

Even with these policy and clinical efforts, early diagnosis is still not an easy task. In practice, clinicians usually rely on a combination of imaging tests, cerebrospinal fluid examination, and cognitive assessments. Each of these methods has its own problems. For example, lumbar puncture is invasive and not always acceptable to patients. PET imaging is useful but expensive and not widely available in many hospitals. Cognitive tests also depend quite a lot on the examiner and sometimes even on the patient's short-term condition on the day of testing [6–7]. Because of these practical issues, there has been ongoing interest in methods that are simpler to apply but still reasonably reliable.

This is probably one of the reasons why artificial intelligence (AI) has started to attract attention in this field. AI is often described as being able to handle large and complex datasets, which traditional statistical methods struggle with. Most current studies still rely on machine learning or deep learning approaches [8]. Methods like support vector machines (SVM), random forests (RF), and logistic regression are still used quite often, especially in earlier or smaller-scale studies. But in more recent work, deep learning seems to be taking a more central role, particularly when dealing with imaging or multimodal data.

Convolutional neural networks (CNNs) are probably the most commonly used deep learning method in this area. They are mainly applied to MRI and PET scans to detect structural atrophy or metabolic abnormalities in the brain [8–9]. In the last few years, there has also been a shift toward combining different types of data. Instead of relying only on imaging, researchers are now bringing together blood biomarkers, genomic data, and other clinical information. These multimodal approaches are often considered more realistic, although they are also more difficult to standardize in practice [10]. On top of that, newer tools like

generative AI and large language models have started to appear in AD-related research. At this stage, their use is still mostly exploratory, but they are being tested in areas such as clinical support, patient communication, and broader digital health applications [11–12].

2. AI Applications in early diagnosis of AD

2.1. AI-assisted neuroimaging diagnosis

Neuroimaging has been used for quite a long time in the study of Alzheimer's disease (AD), especially in clinical settings. In general, MRI is mainly used to observe structural changes in the brain, such as atrophy in areas like the hippocampus and entorhinal cortex. PET imaging is usually discussed in relation to amyloid-β (Aβ) deposition and Tau-related changes. These are fairly standard applications, but in practice the interpretation of images is not always very clear-cut. In real clinical work, the reading of scans often depends on the experience of the clinician or radiologist. So the same image may not always lead to exactly the same conclusion, which is something often mentioned in the literature. Because of this kind of variability, there has been increasing attention on whether computational methods could help with interpretation, especially deep learning-based approaches for neuroimaging analysis in AD research [9, 13–14].

Some of the early deep learning studies tried to pick up imaging patterns that are not obvious by visual inspection. For example, Pan et al. reported a kind of spatial progression pattern in structural MRI data, suggesting that changes may start from medial temporal areas and then extend outward toward the neocortex [9]. It is not an entirely new idea, but their large dataset makes the pattern more convincing. In another study, Hu et al. did not rely on just one type of feature [15]. They mixed radiomics features, deep learning representations, and clinical variables together, and built a multi-task model that could classify four stages of disease progression. The reported external AUC was 94.2%, which is relatively high compared to many earlier models. There are also studies that go beyond classification. Lee et al., for instance, tried to generate Tau-PET images using other imaging modalities such as T1 MRI, FDG-PET, and amyloid PET [16]. Interestingly, the version based on FDG inputs performed better than the others.

Besides single-model or single-modality work, multimodal approaches are becoming more common now. The idea is basically to combine different types of information instead of relying on one source. Xue et al. proposed a Transformer-based model trained on a very large dataset (over 50,000 individuals from multiple cohorts) [10]. Their model was able to separate 10 dementia subtypes with an AUROC of 0.96. They also mentioned that it could help clinicians in practice, although how much it actually improves decision-making in real settings still needs more validation. In a somewhat similar direction, Cao Gongpeng et al. used a dual-path convolutional network with adaptive feature fusion [17]. Their model was not only used for AD classification but also for predicting conversion from mild cognitive impairment (MCI) to AD.

There are also several review papers that try to summarize what is going on in this area. Pan Pian et al. focused on MRI–PET combined methods and how deep learning is being used for early detection and staging [13]. Qian Chengyi et al. reviewed image-based classification models, including CNNs, ResNet, and Transformer-based architectures [14]. Chen Chong et al. took a broader view and discussed how AI is gradually being integrated into medical imaging practice in general, with a focus on efficiency and reducing differences between observers [18].

2.2. AI-assisted biomarker identification

In Alzheimer's disease (AD) research, finding biomarkers that are easy to access and still reliable has become a key direction. At present, several markers are often discussed, including amyloid-β (Aβ42), different phosphorylated tau forms such as p-Tau181 and p-Tau217, and neurofilament light chain (NfL). These are usually linked to core pathological changes in AD, although their roles are not exactly the same. Recently, there has been more attention on blood-based biomarkers, especially plasma p-tau217. One reason is that it might offer information similar to cerebrospinal fluid tests, which are more invasive in practice [19–21].

Across different studies, plasma p-tau217 has been tested in various settings and with different methods. Palmqvist et al. reported results from several cohorts in Sweden and Spain, and the marker seemed to distinguish AD pathology with accuracy around 0.90–0.94 [19]. Ashton et al. also found strong performance using a Simoa-based assay, with AUC values above 0.95 in multiple datasets [20]. Barthelemy et al. took a slightly different approach using mass spectrometry, and their results were broadly consistent with cerebrospinal fluid measurements, sometimes even a bit better, although the differences were not always large [21]. Hansson et al. provided a more general discussion, mainly focusing on how blood biomarkers are moving from research studies into more clinical-type applications and trials [22].

Apart from measuring biomarkers themselves, some studies try to use AI methods to make better use of the data. For example, Cai et al. looked at longitudinal data from a Chinese cohort and also a familial AD cohort [23]. They found that plasma Aβ42, p-tau181, and NfL together could give some prediction signal several years before symptoms actually appear (up to about eight years in their report). Zhang Mengguo et al. also explored combinations of markers, especially p-tau181, Aβ42, and NfL, and tried to see how well they work together in identifying early or preclinical AD cases [24].

More recently, people have also started mixing biomarker data with other types of information instead of treating them separately. Jasodanand et al. proposed a Transformer-based model that combined plasma Aβ42/40 ratios, MRI features, and cognitive test scores [25]. One small technical detail they mentioned is a random feature masking strategy, mainly to deal with missing data, which is actually quite common in clinical datasets.

2.3. AI-assisted digital behavioral assessment

Traditional cognitive scales are still widely used in Alzheimer's disease (AD) assessment, but they are not always stable in practice. The results can be affected by many small factors, such as how the examiner conducts the test, the patient's mood or cooperation level on that day, and even the testing environment. Because of this, researchers have been looking more at digital behavioral signals that might reflect cognitive changes in a more continuous and less subjective way. These signals include things like speech, walking patterns, sleep data, and hand movements, which are now being analyzed with different AI methods [26–29].

Speech analysis seems to be one of the more active directions. It is often said that language changes appear quite early in cognitive decline, although this is still being studied. Hajjar et al. used speech recognition combined with machine learning to extract features from speech data, and they found some links between these features and both cerebrospinal fluid biomarkers and imaging results [26]. Garcia-Gutierrez et al. also worked on speech data across different stages of AD [27]. They focused on paralinguistic features, and their results suggested that speech patterns could separate different levels of cognitive impairment, though the boundary is not always very clear in real cases.

With the development of large language models (LLMs), the scope of behavioral analysis has become broader. Instead of only structured test data, some studies now try to use routine clinical text or records. Du et al. showed that LLM-based analysis of clinical notes might help identify early cognitive decline in older adults, although this is still more of an exploratory application [11]. Treder et al. reviewed this direction and pointed out that LLMs are being explored not only for cognitive assessment but also for communication and clinical support tasks, though most of the work is still in early stages [12].

There are also quite a few review studies summarizing digital biomarkers more generally. Qi et al. looked at a large number of studies (over 400), and only part of them actually used AI methods, but the trend is clearly increasing [28]. They reported an average AUC around 0.887, although this varies quite a bit across studies. Ran Longfei et al. also summarized digital technologies in AD, including wearable devices, virtual reality, and machine learning methods [29]. Gait-based analysis in particular is often mentioned for distinguishing mild cognitive impairment (MCI) from AD, but again, performance is not always consistent depending on the dataset.

3. AI applications in AD disease course prediction and monitoring

AD is a progressive neurodegenerative disorder, and longitudinal monitoring plays an important role in tracking disease evolution. Artificial intelligence methods have been applied to longitudinal clinical, imaging, and biomarker data to estimate changes in cognitive function over time [30–36].

3.1. Prediction of MCI-to-AD conversion

Some studies have tried to use machine learning models to predict how mild cognitive impairment (MCI) might progress to Alzheimer's disease (AD), especially in the earlier or preclinical stages. Mattsson-Carlgren et al. used plasma p-tau217 together with other biomarkers to estimate longitudinal cognitive decline [30]. The focus was not only on diagnosis but more on the trajectory, although the prediction accuracy still depends on the dataset and setting. Lee et al. combined several types of data, including neuroimaging, cognitive tests, and genetic information [31]. Compared with single-source models, their multimodal approach performed better in predicting conversion from MCI to AD, with an AUC above 0.92. Karlsson et al. also worked in a similar direction [32]. They used plasma p-tau217, MRI, and clinical variables to estimate tau deposition (tau-PET), which is interesting because it tries to replace PET-based measurement with a model-based estimation, although this is still an indirect approach.

3.2. Electronic medical records and real-world data monitoring

Another line of work uses electronic medical records and other real-world data instead of controlled research datasets. The idea is basically to see whether routine clinical data can already give early warning signals. Tudor Car et al. built a machine learning model based on large-scale longitudinal EHR data and reported that some risk signals may appear years before an official AD diagnosis, although how reliable these early signals are still needs more validation [33]. Han Yingmei et al. reviewed different deep learning methods for AD staging and progression prediction using real-world or longitudinal data [34]. They covered CNNs, RNNs, and also hybrid models that try to handle time-series information. In practice, these models often look good on paper, but performance can vary quite a bit depending on how the data is collected and cleaned.

3.3. Remote monitoring and smart devices

With telemedicine and wearable devices becoming more common, there is also interest in monitoring AD patients outside hospitals. Instead of only relying on scheduled clinical visits, researchers are starting to look at daily-life data, such as movement or home activity patterns. The idea is still developing, and many systems are not yet widely used in clinical settings. Shaik et al. reviewed different types of technologies used for this purpose, including wearable sensors, smart home systems, and environmental monitoring tools [35]. They also discussed how these systems might be connected to clinical workflows, although in reality this integration is still quite limited in many places. Overall, continuous data collection from real-world environments, when combined with AI analysis, may help track changes over time, but most studies are still at the exploratory stage.

4. AI applications in AD treatment and drug development

At present, available therapeutic options for Alzheimer's disease (AD) remain limited in their disease-modifying effects. In this context, artificial intelligence has been applied in several stages of drug development, including target identification, compound screening, drug repurposing, and network pharmacology analysis [36–40].

4.1. AI-Assisted drug screening and target prediction

Cheng et al. reviewed the integration of artificial intelligence with open science approaches in AD drug discovery, focusing on the use of large-scale biomedical data across different stages of the drug development pipeline [36]. Abramson et al. introduced AlphaFold 3, which employs a diffusion-based architecture for protein complex structure prediction [37]. In AD-related research, it has been used for structural modeling of Aβ and tau aggregation regions, supporting protein-level target analysis.

4.2. AI-driven drug repurposing

Li et al. proposed the DeepDrug framework for AI-based drug repurposing [38]. The model encodes biomedical knowledge graphs using graph neural networks and was applied to identify a multi-drug combination for AD involving pathways related to neuroinflammation, mitochondrial function, and glucose metabolism. Drug repurposing approaches are often used to explore existing compounds for new therapeutic indications in AD research.

4.3. AI-assisted traditional Chinese medicine network pharmacology

Zhang et al. reviewed AI-based network pharmacology methods, including network relationship mining, target localization, and target navigation [39]. These methods have been applied to explore potential mechanisms of traditional Chinese medicine (TCM) formulas in AD. Chang Qingqing et al. analyzed the Babao Yizhi Formula using network pharmacology and molecular docking, identifying 194 active components and 1,071 protein targets, including AKT1, TP53, IL6, TNF, and IL1β [40].

5. Current challenges

Despite the rapid expansion of AI applications in Alzheimer's disease (AD), several issues continue to limit

their broader clinical implementation [41–45]. Challenges related to data quality, model transparency, and ethical governance remain subjects of ongoing discussion and research.

5.1. Data heterogeneity and insufficient model generalization

One of the problems that keeps coming up in medical AI studies is that models often do not behave the same when they are moved from one hospital or dataset to another. This is not very surprising, but it is still a big issue. Differences in imaging protocols, how data is collected, diagnostic standards, and even how labels are assigned can all affect the final performance of a model.

Mittermaier et al. looked at different kinds of bias in medical AI systems [41]. They pointed out that bias can appear at multiple stages, including data collection, labeling, and also during model development itself. They also listed several possible ways to deal with this. Some methods are more technical, like adversarial training or fairness-aware learning, which try to reduce bias inside the model. Others are more about system design, for example federated learning or multi-center collaboration, which try to bring in more diverse data. Even so, in practice, it is still hard to get large and balanced AD datasets. Many regions simply do not have enough data, or the data quality is not consistent.

5.2. Model interpretability

As deep learning models become more complex, it is also harder to explain how they make decisions. This is a common concern in clinical use. Doctors usually want to know not just the output, but also why the model gives a certain prediction.

Taiyeb Khosroshahi et al. reviewed several explainable AI methods in AD neuroimaging studies, such as SHAP, LIME, Grad-CAM, LRP, and Integrated Gradients [42]. Each method has slightly different outputs and computational costs, but they all try to make model decisions more understandable in some way. Still, most of the evidence so far comes from retrospective datasets like ADNI, which is kind of standard in this field. Real prospective validation is still not very common, and this part is still developing.

5.3. Ethical and privacy considerations

Besides technical issues, there are also concerns about privacy and regulation when using AI in healthcare. These issues are not purely technical and often overlap with legal and ethical questions.

Muehlematter et al. reviewed FDA-approved AI or machine learning medical devices and found that many of them were originally not designed as “AI systems” in the strict sense, which reflects how messy the regulatory situation actually is [43]. Other studies also discuss broader ethical issues in large medical AI models, including data privacy, decision-making support, and possible impacts on doctor–patient relationships [44]. Health inequality is also mentioned quite often, although it is not always easy to measure directly.

To address these problems, people have proposed things like better data governance rules, clearer regulatory frameworks, and improved system design. Privacy-preserving approaches are also being explored. For example, Pan et al. used federated learning to predict MCI-to-AD conversion across multiple institutions, while keeping the data locally stored. It shows one possible direction, although it is still not widely used in real clinical systems [45].

6. Conclusions and prospects

The use of artificial intelligence in Alzheimer's disease (AD) research has been growing in the last few years. It is being applied in quite a few areas now, like early diagnosis, tracking disease changes over time, and also some attempts in drug-related research. Between around 2023 and 2026, more papers keep appearing in these directions, but honestly, the progress is not really balanced across them.

For imaging work, many recent studies have moved toward multimodal models, especially those based on Transformers. The general idea is to improve differentiation between different dementia types, but the performance is still quite dependent on the dataset and how the model is trained. Blood biomarkers look a bit more stable in comparison. Plasma p-tau217 in particular keeps showing relatively good results in different studies, so it is often mentioned as a promising, less invasive option, although it is still not fully settled in clinical use. For behavioral or cognitive assessment, the direction is also shifting a bit. Instead of only structured tests, some work now tries to use large language models on clinical notes or free text, but this area still feels quite early and a bit exploratory. On the therapeutic side, there are also some early-stage studies combining generative AI with structural biology tools like protein structure prediction (for example, AlphaFold 3), mostly for target identification or early drug design ideas rather than anything clinical yet.

Even with all these developments, a few problems keep coming up again and again. Data imbalance is probably one of the most obvious ones. Large multi-center datasets are still not easy to get, and some regions still contribute very limited data, including parts of developing countries such as China. Because of this, models often do not transfer well outside their original setting. Another issue is that different research directions do not really connect with each other. Imaging studies, biomarker studies, and digital health studies are still mostly separate lines of work, and there is not really a unified pipeline that links screening, diagnosis, and treatment in a continuous way. Interpretability is another concern, especially for deep learning models, which are still hard to explain in a clinical sense. And then there are also broader issues like data standards, regulation, and privacy, which are often mentioned but still not clearly resolved.

Overall, AI in AD research is definitely moving forward, but the direction is not very linear. Some areas are moving faster, some are still quite early, and some feel a bit disconnected from each other. Whether it will actually become useful in routine clinical work is still unclear. It probably depends not only on how good the models are, but also on whether these more practical problems can be sorted out in a way that actually works in real hospitals and across different systems.

Disclosure statement

The authors declare no conflict of interest.

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