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REVIEW

Exploring Intervention Techniques for Alzheimer's Disease: Conventional Methods and the Role of AI in Advancing Care

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Abstract: Alzheimer's disease (AD) is a neurodegenerative condition characterized by cognitive decline and functional impairment. This study compares conventional intervention techniques with emerging artificial intelligence (AI) approaches to AD. Intervention technique refers to a specific method or approach employed to bring about positive change in a particular situation. In the context of AD, such techniques are crucial as they aim to slow down the progression of symptoms, alleviate behavioral challenges, and support patients and their caretakers in managing the complexities of the condition. Conventional intervention techniques, such as cognitive stimulation and reality orientation, have demonstrated benefits in improving cognitive function and emotional well-being. Conventional intervention approaches are widely preferred as they have a proven track record of effectiveness, personalized response, cost-effectiveness, and patient-centered care. Despite these benefits, they are limited by individual variability in response and long-term effectiveness. On the other hand, AI-based approaches such as computer vision and deep learning hold the potential to revolutionize Alzheimer's interventions. These technologies offer early detection, personalized care, and remote monitoring capabilities. They can provide tailored interventions, assist decision-making, and enhance caregiver support. Although AI-based interventions face challenges such as data privacy and implementation complexity, their potential to transform Alzheimer's care is significant. This research paper compares conventional and AI-based approaches. It reveals that while traditional techniques are well established and have proven benefits, AI-based interventions offer novel opportunities for personalized and advanced care. Combining the strengths of both approaches may lead to more comprehensive and effective interventions for individuals with AD. Continued research and collaboration are crucial to harness the full potential of AI in improving Alzheimer's care and enhancing the quality of life for affected individuals and their caregivers.

Keywords: Alzheimer's disease, intervention techniques, conventional methods, artificial intelligence, cognitive stimulation, reality orientation, reminiscence therapy

1. Introduction

Alzheimer's disease (AD) is a neurodegenerative disorder characterized by progressive cognitive decline, memory loss, and impairment in daily functioning (Mormino et al., 2009). With the global prevalence of AD expected to rise in the coming years, there is an urgent need for innovative interventions to improve care and support for affected individuals and their caregivers. In recent years, the integration of conventional interventions with advanced technologies, such as DL, vision transformers (ViTs), natural language processing (NLP), and machine learning (ML) techniques, has shown promising potential for enhancing Alzheimer's interventions (Jack et al., 2018). This introduction will provide an overview of these approaches and their application in the context of AD, highlighting the benefits and challenges associated with their integration.

Conventional interventions for AD have long been employed to address cognitive decline, maximize functional independence, and enhance the quality of life for individuals with the condition. Cognitive stimulation therapy, for instance, involves engaging individuals in various cognitive exercises and activities to maintain cognitive abilities and foster social interaction (Spector et al., 2011). Reminiscence therapy (RT) focuses on stimulating memories and promoting a sense of identity through photographs, music, and storytelling (Woods et al., 2018). These interventions have demonstrated positive effects on cognition, mood, and overall well-being in individuals with AD.

DL, a subset of ML, has gained significant attention in recent years due to its ability to analyze complex patterns and learn from large datasets. DL techniques have been employed in various domains, including medical imaging, genomics, and clinical records. For instance, DL models trained on neuroimaging data have shown promising results in accurately detecting and predicting AD progression (Cheng et al., 2015). These models can identify subtle changes in brain structures and biomarkers, enabling early diagnosis and intervention.

ViT, a novel architecture within computer vision, has emerged as a powerful tool for analyzing visual data. Unlike traditional Convolutional Neural Networks (CNNs), which operate on fixed-sized grids, ViTs employ self-attention mechanisms to capture long-range dependencies within images. This capability makes them well suited for tasks such

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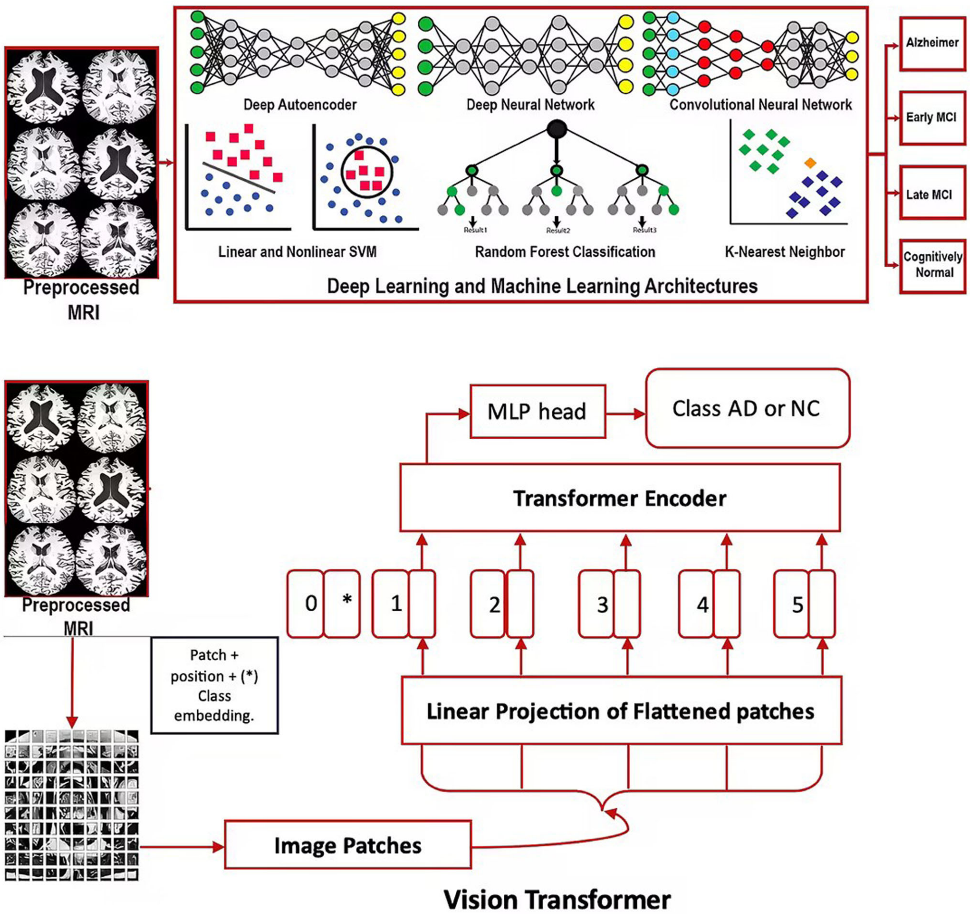
as object detection, image segmentation, and classification. ViT for AD can be utilized to analyze medical imaging data, enabling the detection of neurodegenerative changes and abnormalities associated with the disease (Xing et al., 2022). The ViT architecture is assessed for AD detection. The original version of the model was developed for NLP tasks. However, the development of its adaptation to computer vision tasks is being implemented at a fast pace. Efficient algorithms for AD diagnosis, and early detection, in particular, are a pivotal area in medical imaging research. The study by Xing et al. (2022) evaluates the potential of the ViT model for processing multimodal positron emission tomography (PET) images, such as Florbetapir (AV45) and fluorodeoxyglucose (FDG) PET imaging are valuable techniques to detect the amyloid-β (Aβ) load and brain glucose metabolism in patients with Alzheimer's disease (AD) and PET-fluoro-D-glucose. It is suggested that the use of the ViT model together with the self-attention mechanism and 3D-to-2D conversion module will enhance both the efficiency and accuracy of AD diagnosis. By leveraging the power of ViT, more accurate and efficient analysis of visual data can be achieved.

NLP, another branch of AI, focuses on understanding and generating human language. NLP techniques have been extensively used in various healthcare domains, including AD research. In the context of Alzheimer's interventions, NLP can be employed for tasks such as language modeling, sentiment analysis, and text generation. For instance, NLP models can generate personalized narratives, reminders, and instructions tailored to individuals with Alzheimer's, aiding in memory retention and daily task management. NLP can also facilitate natural language interactions and communication, improving engagement and social interactions for individuals with Alzheimer's.

ML techniques encompass a wide range of algorithms and approaches that enable computers to learn from data and make predictions or decisions. ML techniques for AD detection have been applied to various data sources, including genetic information, clinical records, and behavioral data (Cheng et al., 2015). These techniques can be utilized for tasks such as early detection, predicting disease progression, and personalizing treatment strategies. The articles by Shaffi et al. (2024) explore ML techniques on the AD Neuroimaging Initiative (ADNI) and Open Access Series of Imaging Studies (OASIS) datasets to classify AD stages. The results show that a smaller number of diverse ML ensembles outperform the state-of-the-art CNN-centric models (Shaffi et al., 2022).

The integration of these advanced technologies with conventional interventions holds great promise for enhancing Alzheimer's interventions. By leveraging DL, ViT, NLP, and ML techniques, we can achieve more accurate cognitive assessments, early diagnosis, personalized care, improved communication, and enhanced caregiver support. A simple representation in Figure 1 demonstrates the working of DL, ML, and ViT in the prediction of AD. However, the integration of these approaches also presents challenges, including data privacy and ethical considerations, the interpretability of AI models, and the need for interdisciplinary collaboration among healthcare professionals, researchers, and technologists.

Figure 1
Demonstrating the working of different AI techniques in predicting AD



In this comprehensive review paper, we present a concise yet informative overview of various intervention techniques for AD, encompassing both conventional methods and cutting-edge approaches powered by AI. By synthesizing the latest research findings, our review aims to offer a valuable resource for researchers and clinicians, providing insights into the current state of the art in AD intervention. Tailored to benefit both seasoned professionals and newcomers to this dynamic field, the paper serves as a reference guide, fostering a deeper understanding of the diverse strategies employed in the ongoing quest to address the challenges posed by AD.

The rest of the manuscript is organized as follows: Section 2 discusses the motivation and proposed plan. Section 3 presents the survey of conventional intervention techniques. Section 4 presents the survey of intervention techniques based on AI techniques. Important findings of the survey are discussed in Section 5, future works discussed in Section 6, and conclusions are drawn in Section 7.

2. Motivation and Proposed Plan

The worldwide insurgence of neurodegenerative disorders and the urgent need for efficient diagnostic and intervention strategies are driving exponential growth in the field of AD research. With the significant growth of the aging population, the impact of AD on individuals, families, and healthcare systems becomes increasingly profound. This investigation requires inventive, accurate, and prompt techniques for identifying, forecasting, and intervening in AD in conjunction with the integration of AI methods and the pressing need to tackle the significant global health impact of AD. The rapid progress in artificial intelligence (AI) and ML technologies provides unparalleled prospects to transform the conventional diagnostic and intervention approaches for AD. Additionally, early detection, enabled by AI techniques, is paramount for proactive management, potentially leading to timely therapeutic interventions and lifestyle modifications to curtail the progress of AD.

Motivated by the need to address the challenges of AD, this review explores the landscape of intervention techniques using the latest AI advancements. The proposed plan explores the ethical implications and emphasizes patient and caregiver empowerment. The review also seeks to contribute to the responsible and equitable implementation of AI-driven interventions in the context of AD, ultimately advancing the collective efforts to combat this devastating neurodegenerative disease. In addition to reviewing conventional intervention techniques, we scrutinize both traditional and cutting-edge AI methodologies, providing a comprehensive synthesis of the current state of AI tools and driving the discourse toward innovative solutions that potentially transform the landscape of AD diagnosis and care.

This paper thoroughly examines AD interventions by comparing conventional methods with emerging AI-based approaches. While recognizing the effectiveness of traditional techniques, the article also sheds light on their limitations on individual differences and long-term impact. In contrast, AI technologies like computer vision and DL offer exciting possibilities like remote monitoring, early detection, and personalized care. Despite data privacy challenges and other obstacles, these advancements show great potential for revolutionizing Alzheimer's care.

The article emphasizes the importance of extensive research and collaboration to fully harness the capabilities of AI in transforming Alzheimer's interventions. Integrating traditional and advanced methods is the key to providing comprehensive and effective support, combining the familiarity and cost-effectiveness of conventional techniques with the innovation of AI. By merging these approaches, the article supports improved early detection, personalized care, and overall outcomes for Alzheimer's patients. The scientific community's contribution is critical to the ongoing development of intervention techniques, which is vital in the continued pursuit of enhancing the lives of individuals affected by this devastating disease.

3. Conventional Intervention Techniques

Conventional intervention techniques for AD encompass a multifaceted array of strategies designed to enhance the quality of life and cognitive capabilities of those affected by the condition. Various strategies are categorized to address different aspects of well-being and support. These categories include cognitive engagement, technology assistance, therapies, physical well-being, mindfulness and mental health, communication support, personal interventions, and environmental and caregiver support (Figure 2). Each category is crucial in providing comprehensive care, contributing to the holistic management of AD. This section explores the specifics of each intervention category to clarify their distinct contributions and benefits.

Figure 2
Categories of conventional intervention techniques for Alzheimer's disease

3.1. Cognitive engagement

Cognitive stimulation therapy involves engaging individuals in activities and exercises to improve cognitive functioning, memory, and problem-solving skills (Spector et al., 2010). The article by Yates et al. (2014) describes the development of individual cognitive stimulation therapy (iCST) for dementia, a home-based intervention delivered by caregivers, based on the Medical Research Council framework for complex interventions. The authors reviewed the existing evidence and theory on group and individual cognitive stimulation and consulted with stakeholders and experts. They field-tested the iCST materials with 24 days of people with dementia and their caregivers. The iCST program consists of 75 sessions covering 14 themes and includes a toolkit with a guide for caregivers. The authors report the fundamental changes and feedback from the development process and outline the ongoing evaluation of iCST in a large-scale randomized controlled trial (RCT). The systematic review discussed in Wang et al. (2022) narrates cognitive interventions for AD. Cognitive training positively impacts global cognitive function and short-term depression in the short, medium, and long term, but consistent conclusions for other cognitive outcomes are lacking.

Reality orientation (RO) in combination with standard treatment is one of the methods that might be effective in terms of improving cognitive outcome for AD patients. In the study by Camargo et al. (2015), patients with AD symptoms who received RO sessions once a week over a period of six months along with acetylcholinesterase inhibitors developed significant cognitive improvements if compared with the control group. It seems that RO is a very effective supplementary intervention in the management of dementia among patients with AD.

The authors Rao and Khan (2022) conducted a systematic review to analyze the efficacy of emotion therapies among individuals with dementia. The review examined 18 studies and focused on various therapies, including simulated presence, RO, validation therapy, animal-assisted therapy, multisensory stimulation, music therapy (MT), and more. The findings indicated positive effects on behavior, assessments, and quality of life in people with dementia. Several studies demonstrated the effectiveness of emotion therapies in reducing problem behaviors, improving cognition, and enhancing mood. Emotion therapies such as MT, multisensory stimulation, and mindfulness-based stress reduction were particularly notable for their positive impact on depressive symptoms. Despite positive outcomes, some studies reported limitations and the need for further investigation, especially concerning severe dementia cases. The authors recommended integrating emotion therapies in dementia care to enhance the well-being of individuals with dementia. The review article by Li et al. (2023) analyzes non-drug interventions for AD over the past decade, including cognitive strategies, physical exercise, brain stimulation, and nutritional supplements, to identify effective approaches for symptom improvement.

Sensory stimulation interventions involve using various sensory stimuli, such as touch, smell, and sound, to engage the senses and enhance cognition and well-being in individuals with Alzheimer's. This review by Hayden et al. (2022) explores sensory interventions for older adults with dementia, revealing ten intervention categories and emphasizing their significance in managing dementia-related challenges. In the review article, Yang et al. (2021) explore the benefits of sensory and multisensory stimulation for AD patients. After analyzing the literature spanning two decades from 2000 to 2020, the article covers various interventions, including MT, aromatherapy, rhythmic stimulation, light therapy, multisensory stimulation, and virtual reality (VR)-assisted therapy. The findings suggest that these interventions effectively enhance AD pathology and memory and improve cognition and behavior. Additionally, these interventions induce brain nerve oscillation, boost brain plasticity, and regulate regional cerebral blood flow. The authors highlight the need for further exploration and improvement of the potential mechanisms and stimulation parameters.

3.2. Technology assistance

Assistive technologies encompass a range of devices and systems that aid individuals with Alzheimer's in daily activities, safety, and communication (Ienca et al., 2017). Expanding on innovative assistive technology, the study by Arthanat et al. (2020) explores a socially assistive robot (SAR) for AD caregivers. The SAR, integrated with Internet of Things (IoT) sensors, demonstrated the potential of addressing caregiving challenges. Caregivers envisioned SARs as next-gen solutions, emphasizing factors like navigability, engagement, adaptability, humanoid features, and interface design. Acceptance revolved around successful navigation, while barriers included technological complexity and system failures. Caregivers recognized SARs' role in aging in place but highlighted the importance of timing, commercial viability, funding, and their connection with care recipients. Long-term home-based research is crucial for validating SARs' impact on the well-being of individuals with AD.

Electronic memory aids include digital calendars, reminders, and voice-activated assistants that help individuals with Alzheimer's manage their daily tasks and appointments (Marziali & Garcia, 2011). In a critical examination of electronic aids for prospective memory in dementia, a study by King and Dwan (2019) showed a promising outcome. The study also underscores the necessity for further device and software refinement to ensure reliability. Small sample sizes in their studies help generalizability, with a notable gap in research within user's home environments. The review advocates for future studies with robust devices that explicitly consider the diverse needs of individuals with dementia. Emphasis should extend beyond aid effectiveness, exploring outcomes such as enhanced daily functioning, improved quality of life, and increased social connectedness.

Individuals with Alzheimer's can stay connected using visual aids, symbol-based communication tools, and voice output systems (Ekström et al., 2017). The study by Yousaf et al. (2020) narrates the realm of mobile health (mHealth) applications catering to dementia, focusing on AD. There are 29 of them curiously selected from 281 articles, unveiling six key mHealth app categories: ADL-based cognitive training, monitoring, dementia screening, reminiscence and socialization, tracking, and caregiver support. Examining 678 commercial apps from the Apple App Store and Google Play Store identified 38 apps that met the inclusion criteria. Despite limited research, the study underscores the promising feasibility and benefits of mHealth apps in enhancing dementia and AD community care.

Global Positioning System (GPS) tracking devices locate individuals with Alzheimer's who may wander and become lost, enhancing their safety and enabling prompt retrieval (Ray et al., 2019). The study by Adardour et al. (2020) presents an innovative IoT prototype, a lightweight dorsal belt equipped with NodeMCU ESP8266, a GPS module, and a WiFi modem/router, enabling real-time location tracking of Alzheimer's patients. Accessible via Android/iOS mobile and web applications, the system utilizes a Kalman filter to estimate the patient's position, which is crucial for outdoor movements. The research underscores the prototype's efficacy, offering a promising solution to enhance patients' quality of life and support caregivers in their responsibilities.

Ambient assisted living (AAL) systems use sensors and smart home technologies to support individuals with Alzheimer's in their living environment, ensuring safety and providing reminders (Blackman et al., 2016). The article by Lussier et al. (2020) investigates the concurrent validity of AAL monitoring reports compared to an observation by a caregiver monitoring a 90-year-old Alzheimer's patient, revealing evolving trends in daily activities around 490 days. AAL reports identified significant changes, some unnoticed by the clinical nurse, demonstrating concurrent validity. The study underscores AAL's potential to offer clinically relevant information over time, aiding decision-making in healthcare services and supporting aging in place by addressing the unique challenges of Alzheimer's patients. Herzog (2023) has focused on addressing mild cognitive impairment (MCI), which affects over 15% of people aged 65 years and over. He suggests using AAL systems to help manage MCI and assesses their feasibility through an online questionnaire aimed at healthcare professionals. The results indicate strong support for implementing general AAL solutions for MCI patients.

VR technology creates immersive and interactive environments for individuals with Alzheimer's to enhance cognitive stimulation, reminiscence, and relaxation (Garcia-Betances et al., 2015). In the pilot RCT, Oliveira et al. (2021) examine the impact of a two-month VR cognitive stimulation program on individuals experiencing mild-to-moderate dementia due to AD. The study involved 17 participants randomly assigned to experimental and control groups. The VR intervention was designed to replicate daily life activities and comprised ten sessions over two months. Through baseline and follow-up neuropsychological assessments targeting memory, attention, and executive functions, the authors' preliminary findings indicate a significant enhancement in overall cognitive function within the experimental group. The observed large effect size in global cognition suggests the potential effectiveness of VR-based cognitive stimulation for older adults with dementia, emphasizing its role in preserving cognitive function in the context of AD.

3.3. Therapies

Validation therapy focuses on empathetic communication and validating the emotions and experiences of individuals with Alzheimer's, promoting a sense of self-worth and reducing distress (Neal et al., 1996). The review by Goodarzi et al. (2019) addresses AD and the need for effective therapeutic strategies. Focusing on regenerative medicine, the authors emphasize the significance of preclinical stages to validate novel approaches. The review underscores the importance of ethical guidelines in animal studies for understanding biological mechanisms and achieving meaningful outcomes. It provides insights into developing and validating suitable AD animal models, which are crucial for advancing regenerative medicine in the context of this prevalent neurodegenerative disorder. Kasula (2023) focuses on a ML approach for AD diagnosis and prognosis, integrating various data sources. The proposed model accurately classifies AD stages and differentiates patients from healthy individuals with high accuracy, sensitivity, and specificity. It also demonstrates promise in predicting disease progression and estimating future outcomes, providing valuable insights for personalized treatment planning.

RT involves recalling and discussing past experiences to stimulate memories, improve mood, and enhance social interaction (Woods et al., 2018). The study by Cammisuli et al. (2022) explores the efficacy of RT in AD through the analysis of five randomized controlled trials. Administered individually or in groups for 30–35 min/week over 12 weeks, RT significantly improves global cognition, alleviates depression, and enhances the quality of life. While results highlight RT's potential as a non-pharmacological intervention, the limited number of long-term studies calls for further research. The therapy's cost-effectiveness and positive impact on AD individuals emphasize its role in comprehensive care.

Music therapy involves using music and musical activities to stimulate cognitive function, emotional well-being, and social interaction in individuals with Alzheimer's (McDermott et al., 2013). The article by Matziorinis and Koelsch (2022) provides an extensive review of the potential therapeutic benefits of MT for individuals with AD. Focusing on the unique preservation of musical memory in AD patients, the authors explore how MT can positively impact mood, reduce depressive symptoms, and enhance various cognitive functions. They highlight the ability of music to evoke emotions and memories, providing a meaningful avenue for individuals with AD to connect with their identity. The review explains three plausible neural mechanisms underlying the positive effects of music interventions, including neurogenesis stimulation, dopamine release, and modulation of inflammatory processes. The authors conclude by introducing the ongoing Alzheimer's and Music Therapy Study (ALMUTH), which seeks to deepen our understanding of the influence of MT on brain aging, cognition, and mood in those at risk for AD.

Art therapy utilizes artistic activities such as painting, drawing, and sculpture to promote self-expression, improve mood, and enhance communication for individuals with Alzheimer's (Beard, 2012). Art therapy, recognized as a non-pharmacological complementary treatment, demonstrates clinical efficacy in mental disorders. The study by Hu et al. (2021), based at the Shenzhen Technology University and Guangzhou University of Chinese Medicine, systematically explores art therapy's theoretical basis, clinical applications, and prospects through a PubMed search. Focusing on painting and drawing as therapeutic media, the review of 413 articles reveals positive outcomes in mental disorders, including depression, anxiety, cognitive impairment, dementia, AD, schizophrenia, and autism. Art therapy emerges as a valuable method for patients to express emotions and as an adjunct diagnostic tool for medical specialists, suggesting substantial potential for further exploration in clinical applications.

PET therapy involves interactions with trained animals, such as dogs or cats, to provide comfort, reduce anxiety, and improve social engagement in individuals with Alzheimer's (Filan & Llewellyn-Jones, 2006). A seven-year retrospective study spanning 2012 to 2019 by Santaniello et al. (2020) investigated the impact of animal-assisted therapy (AAT) on 127 mild-to-moderate AD patients. The participants were divided into three groups: an AAT group receiving interventions adapted to RO therapy (ROT), a ROT-only group, and a control group. Weekly sessions over six months showed significant improvement in cognitive function (assessed by Mini-Mental State Examination (MMSE)) and reduction in depressive states (evaluated by Geriatric Depression Scale) in the AAT group compared to ROT and control groups. The study highlights the potential of AAT, particularly in enhancing cognitive deficits associated with AD.

3.4. Physical well-being

Exercise and physical activity interventions promote physical fitness and mobility, improve cognitive function, and reduce behavioral symptoms in individuals with Alzheimer's (Groot et al., 2016). In the article, Jia et al. (2019) explore the cognitive effects of physical activity and exercise on AD patients. The study, comprising 13 RCTs with 673 subjects diagnosed with AD, reveals a statistically significant improvement in cognition, as measured by the MMSE score, in intervention groups compared to control groups. The study underscores the positive impact of physical activity and exercise on cognition in older adults with AD, emphasizing the need for further rigorous research to establish optimal intervention parameters.

3.5. Mindfulness and mental health

Mindfulness and meditation cultivate present-moment awareness and promote relaxation and emotional well-being in individuals with Alzheimer's (Wells et al., 2013). The systematic review by Chen et al. (2020) outlines an investigation into the potential efficacy of meditation for AD and MCI. The study conducts a comprehensive search of databases up to March 2020, including RCTs evaluating meditation interventions for AD and MCI patients. The primary outcomes focus on cognitive measures, including the MMSE, and the study aims to provide high-quality evidence on the effectiveness and safety of meditation as an intervention for cognitive impairment among AD and MCI patients.

3.6. Communication support and personal interventions

Assistive communication devices include technologies such as speech-generating devices and picture-based communication aids to support individuals with Alzheimer's in expressing their needs and preferences (Bourgeois & Hickey, 2009). The study by Gulapalli and Mittal (2022) explores non-invasive techniques for AD detection, focusing on speech features analyzed through ML classifiers. Traditionally, AD diagnosis relies on brain medical images, but the authors suggest that spontaneous speech features, including vocal, linguistic, acoustic, and prosodic aspects, could offer an early diagnosis. The article discusses various classifiers and ML algorithms applicable to AD detection, comparing their performance accuracies. The models, developed on diverse datasets, aim to contribute to the advancement of reliable machine assistive technology for healthcare in elderly populations, addressing conditions like AD, Parkinson's disease, vascular dementia, down syndrome, and frontotemporal dementia.

Personalized memoirs that compile photographs, mementos, and written narratives evoke memories and stimulate conversation in individuals with Alzheimer's (Dempsey et al., 2014). Hashim et al. (2013) explore using a personalized digital memory book for RT in AD patients. Integrating multimedia and computer technology, the digital memory book discussed in the article caters to a 67-year-old early-stage Alzheimer's patient, offering information about the patient's family and a multimedia-based guide on performing prayers. The positive response from the patient suggests the effectiveness of this approach. The study advocates further research to enhance content, user interface design, and hardware, highlighting the potential of personalized digital memory books in AD therapy.

3.7. Environmental and caregiver support

Environmental modifications involve adapting to the living environment by removing hazards, providing clear signage, and using cues to support independence and safety for individuals with Alzheimer's (Gitlin et al., 2001). The paper by Ludden et al. (2019) addresses the urgent societal challenge of dementia by proposing a multidisciplinary approach to environmental design for dementia care. While various disciplines have contributed insights, integration is needed to ensure optimal design. The authors conduct a meta-review of recent studies in assistive technology for dementia care and healing environments. They advocate for a user-centered design approach combining meaningful sensory experiences and social engagement through technology-inspired design. Case studies of technology-enhanced prototypes, such as an experienced handrail and a virtual nature installation, demonstrate positive outcomes, emphasizing the potential of this integrated design approach to enhance the well-being of people with dementia and offer novel solutions to their daily challenges.

Caregiver support and training programs provide education, skills, and resources to caregivers of individuals with Alzheimer's to manage the challenges associated with caregiving (Brodaty & Donkin, 2009). For a randomized controlled study, Birkenhäger-Gillesse et al. (2020) assessed the effectiveness of an Australian multicomponent community-based training program adapted for non-medical Dutch healthcare settings. Involving 142 caregiver-patient dyads, the study compared control and intervention groups. While the primary outcome, care-related quality of life, showed no significant difference, caregivers in the intervention group experienced fewer role limitations due to physical and emotional functions and pain reduction. Qualitative analysis revealed positive outcomes, including enhanced acceptance, coping, and improved knowledge of dementia and available community services. This study suggests that while quantitative impacts on care-related quality of life may be limited, qualitative benefits and specific improvements for caregivers are noteworthy. Pasquini et al. (2022) explained that a RCT assesses the impact of a psychosocial intervention on informal caregivers of Alzheimer's patients compared to traditional self-help groups. The study aims to analyze caregiver burden, coping strategies, and well-being, anticipating that the psychosocial intervention group will show more significant improvements.

Table 1 compares various conventional intervention techniques for AD. It includes the names of the methods, a brief description of their techniques, the benefits they offer, and the challenges associated with their implementation.

Table 2 represents the usage ratio of different intervention techniques for three age groups: 50–60, 60–70, and 70–80 years. The usage ratio indicates the percentage of individuals within each age group who utilize a particular intervention technique for managing AD. In the age group 50–60 years, the most used techniques are cognitive stimulation (25%), assistive technologies (35%), electronic memory aids (30%), and communication apps and devices (40%). These individuals rely more on technology-based interventions to support cognitive function and daily tasks. In the age group 60–70 years, there is an increased usage of techniques such as RO (20%), RT (30%), communication apps and devices (30%), and exercise and physical activity (35%). These individuals benefit from interventions that focus on memory stimulation, social interaction, and physical well-being. In the age group 70–80 years, the usage ratio of techniques such as RT (35%), assistive technologies (30%), exercise and physical activity (40%), and mindfulness and meditation (25%) is relatively higher. These individuals may require interventions that promote memory recall, physical health, and emotional well-being. It is important to note that the usage ratios provided in the table are illustrative and may vary depending on individual preferences, healthcare access, and other factors. The table offers a snapshot of the relative popularity of different intervention techniques across various age groups in managing AD. Figure 3 shows a pictorial representation of Table 2.

4. Cutting-Edge Technological Intervention Approaches

Cutting-edge technological interventions in healthcare are witnessing a transformative shift with the integration of advanced technologies such as DL, ML, ViTs, and NLP. These innovative approaches hold significant promise in enhancing our understanding and management of neurodegenerative disorders, particularly AD. Leveraging DL and ML aims to improve diagnostics, treatment, and patient care (Shahbaz et. al., 2019). Incorporating ViT and NLP further extends the capabilities, enabling comprehensive analysis of multimodal data and facilitating

Table 1
Conventional AD intervention techniques

#	Intervention technique	Technique	Benefits	Challenges	Reference
1	Cognitive stimulation	Engaging individuals in structured activities, puzzles, and discussions to stimulate cognitive function and promote social interaction	Enhancing cognitive function and increased memory among older adults with Alzheimer's disease (AD)	Limited long-term effects, individual variability in response, need for trained facilitators	Wang et al. (2022)
2	Reality orientation	Providing orientation cues, calendars, and familiarization with time, place, and person	Valuable non-drug therapy offering potential cognitive and emotional benefits	Limited evidence of long-term effects may cause frustration in some individuals	Li et al. (2023)
3	Validation therapy	Validation of emotions and feelings expressed by individuals with dementia	Improved the accuracy of differential diagnosis and prognostic prediction	Controversial approach, with the potential in reinforcing delusions or false beliefs, requires trained therapists	Kasula (2023)
4	Reminiscence therapy	Using prompts, photographs, and props to stimulate memories and promote discussion	Improved mood, enhanced sense of identity, increased social interaction	Variability in response, potential for emotional distress in some individuals, limited evidence of long-term effects	Woods et al. (2018)
5	Assistive technologies	Use of technological devices such as reminder systems, digital calendars, and voice-activated assistants	Enhanced independence, improved safety, support in daily tasks and routines	Technological complexity, cost considerations, limited accessibility for some individuals	Ienca et al. (2017)
6	Electronic memory aids	Utilization of digital reminders, voice prompts, and memory-assisting devices	Improved memory and task management, enhanced independence, and daily functioning	Technological challenges, difficulty in learning and adapting to new devices, potential reliance on external devices	Marziali and Garcia (2011)
7	Communication apps and devices	Utilization of visual supports, symbol-based communication tools, and voice output systems	Enhanced communication and expression of needs, improved social interaction	Technological complexity, limited customization options, potential difficulties in learning and using new devices	Ekström et al. (2017)
8	GPS tracking devices	Use of location-tracking devices and systems to monitor the whereabouts of individuals with dementia	Enhanced safety, GPS tracking devices offer promising avenues for remote monitoring	Privacy concerns, ethical considerations, potential challenges in device usability and acceptance	Muurling et al. (2021)
9	Ambient assisted living	Implementation of sensor-based systems and smart home technologies to support individuals with dementia	Show promise in effectively assessing and supporting patients with mild cognitive impairment	Cost considerations, privacy concerns, integration with existing infrastructure	Herzog (2023)
10	Virtual reality (VR)	Immersive and interactive experiences using virtual reality technology	Cognitive stimulation, reminiscence, relaxation, improved well-being and mood	Equipment cost, technical expertise requirements, potential for sensory overload	Garcia-Betances et al. (2015)
11	Music therapy	Engagement in musical activities, listening to personalized playlists, and singing familiar songs	Improved mood, reduced agitation, enhanced emotional well-being	Individual preferences and response, challenges in delivering personalized therapy, limited evidence of long-term effects	McDermott et al. (2013)
12	Art therapy	Engagement in artistic activities such as painting, drawing, and sculpture	Enhanced self-expression, improved mood, increased communication and social interaction	Individual variability in response, challenges in adapting to physical limitations, potential for frustration or difficulties in artistic expression	Beard (2012)
13	PET therapy	Interaction with trained animals such as dogs or cats	The valuable non-pharmacological approach in Alzheimer's disease, providing positive outcomes, as revealed in a retrospective	Allergies or fears of animals, infection control considerations, limitations in facility settings	Santaniello et al. (2020)

(*Continued*)

Table 1
(*Continued*)

#	Intervention technique	Technique	Benefits	Challenges	Reference
14	Sensory stimulation	Use of various sensory stimuli such as touch, smell, and sound to engage the senses	Enhanced cognitive function, increased relaxation, reduced agitation and restlessness	Individual response variations, sensory overload concerns, challenges in tailoring stimulation to personal preferences and needs	Hayden et al. (2022)
15	Exercise and physical activity	Regular engagement in physical exercise and activities	Improved cardiovascular health, enhanced cognitive function, reduced behavioral symptoms	Individual physical limitations, adherence challenges, need for tailored exercise programs	Groot et al. (2016)
16	Mindfulness and meditation	Practice of mindfulness techniques and meditation	Reduced stress and anxiety, improved emotional well-being, increased self-awareness	Individual readiness and acceptance, challenges in maintaining regular practice, potential difficulty in individuals with cognitive impairments	Wells et al. (2019)
17	Assistive communication devices	Use of speech-generating devices and picture-based communication aids	Enhanced communication and expression of needs, increased social interaction	Learning curve for individuals with cognitive impairments, customization for individual needs, potential barriers in device acceptance	Bourgeois and Hickey (2009)
18	Personalized reminiscence books	Creation of customized memory books with photographs and narratives	Stimulates memories and conversation, enhances sense of identity and self-expression	Challenges in creating and maintaining personalized books, individual preferences in reminiscence materials	Dempsey et al. (2014)
19	Environmental modifications	Adaptation of the living environment to support independence and safety	Improved safety, reduced confusion, enhanced independence	Cost considerations, limited applicability in shared or institutional settings, individual variations in environmental preferences	Gitlin et al. (2001)
20	Caregiver support and training	Education and training programs for caregivers of individuals with Alzheimer's	Good psychosocial intervention, providing valuable support and training for informal caregivers of older individuals with Alzheimer's disease	Access to support programs, time and resource constraints, caregiver resistance or lack of awareness	Pasquini et al. (2022)

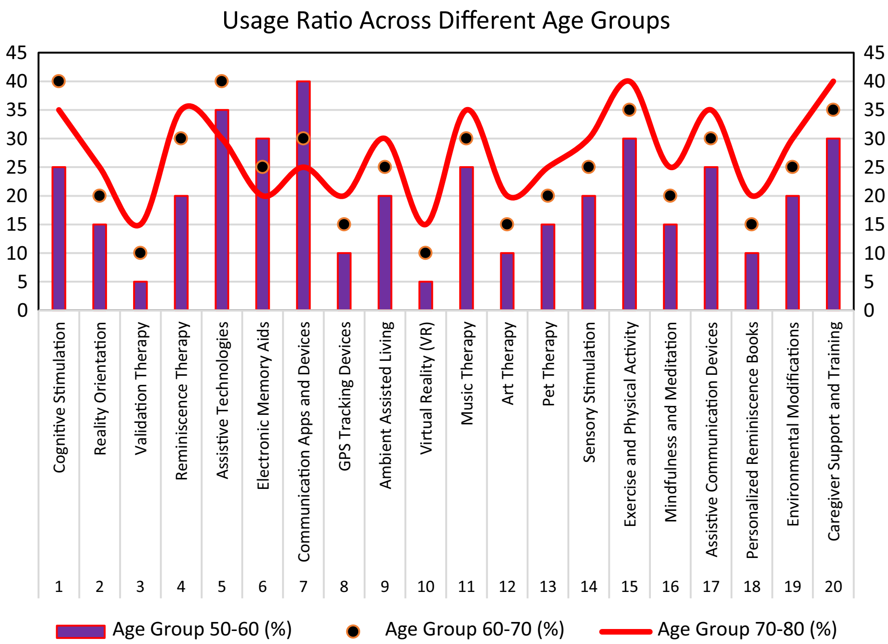
Note: PET, positron emission tomography

Table 2
Hypothetical representation of the usage ratios for each intervention technique across different age groups (50–60, 60–70, and 70–80 years)

#	Intervention techniques	Age group 50–60 years (%)	Age group 60–70 years (%)	Age group 70–80 years (%)
1	Cognitive stimulation	25	40	35
2	Reality orientation	15	20	25
3	Validation therapy	5	10	15
4	Reminiscence therapy	20	30	35
5	Assistive technologies	35	40	30
6	Electronic memory aids	30	25	20
7	Communication apps and devices	40	30	25
8	GPS tracking devices	10	15	20
9	Ambient assisted living	20	25	30
10	Virtual reality (VR)	5	10	15
11	Music therapy	25	30	35
12	Art therapy	10	15	20
13	PET therapy	15	20	25
14	Sensory stimulation	20	25	30
15	Exercise and physical activity	30	35	40
16	Mindfulness and meditation	15	20	25
17	Assistive communication devices	25	30	35
18	Personalized reminiscence books	10	15	20
19	Environmental modifications	20	25	30
20	Caregiver support and training	30	35	40

Note: PET, positron emission tomography

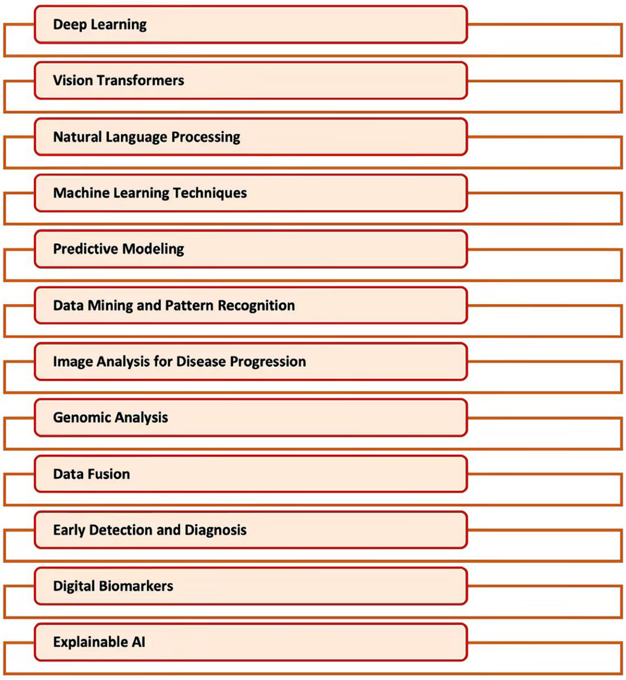
Figure 3
Conventional intervention techniques usage ratio across age groups



a more understanding of complex cognitive conditions. This amalgamation of state-of-the-art technologies represents a frontier in healthcare, offering unprecedented opportunities for early detection, precise intervention, and optimized outcomes for individuals affected by neurodegenerative disorders. This section explores advanced technologies such as DL, ViT, NLP, and ML techniques for intervention approaches in AD, as shown in Figure 4.

DL is a subset of ML that utilizes artificial neural networks with multiple layers to learn and extract complex patterns from data. It has shown promising results in various domains, including healthcare and AD research. DL algorithms can analyze large amounts of medical data, such as brain images or genetic sequences, to aid in diagnosis, disease progression monitoring, and treatment prediction (LeCun et al., 2015). Sharma et al. (2020) introduce the DL-based Internet

Figure 4
Cutting-edge technological intervention approaches



of Health Framework for the Assistance of Alzheimer Patients (DeTrAs), a novel healthcare framework leveraging DL and IoT for personalized assistance to Alzheimer patients. In three phases, it predicts Alzheimer's using a recurrent neural network on sensory data, evaluates abnormality with CNN-based emotion detection and timestamp window-based NL processing, and provides IoT-based assistance. The results indicate a significant 10%–20% improvement in accuracy over existing ML algorithms. The authors show that deeper training with multiple neural network layers contributes to DeTrAs' superior performance. The paper suggests future enhancements, including ambient intelligence and game theoretic approaches for achieving promising further advancements in Alzheimer's patient care within the Internet of Health ecosystem. Another study proposes (Guo & Zhang, 2020) an improved DL algorithm (IDLA) for the early detection of AD using resting-state functional magnetic resonance imaging (R-fMRI) data. The IDLA distinguishes natural aging from disorder progression by utilizing autoencoder networks and clinical text information. IDLA significantly enhances accuracy compared to conventional classifiers, reducing standard deviation by 45%. Incorporating R-fMRI data, the algorithm proves more reliable, providing a promising avenue for early Alzheimer's diagnosis and prevention. The research emphasizes the potential of DL in healthcare and highlights the benefits of improved algorithms in handling high-dimensional information. The paper by Zhao et al. (2023) explores DL integration in PET/MRI for AD. The study highlights DL's potential in image segmentation, reconstruction, diagnosis, and visualization, and it outlines current applications, challenges, and prospects for enhanced AD diagnosis and personalized medicine.

ViTs are a DL model with significant success in computer vision tasks. They use self-attention mechanisms to capture relationships between image patches and learn representations directly from raw image data. ViT has been applied to various medical imaging tasks, including the analysis of brain MRI scans, to identify disease-related patterns and aid in diagnosis (Dosovitskiy et al., 2020). The paper by Xing et al. (2022) introduces Alzheimer Disease Vision Transformer (ADVIT), a novel model designed for AD diagnosis using multimodal PET images. Departing from conventional CNN architectures, the model employs ViT as the backbone for enhanced feature extraction. Integrating PET-AV45 and PET-FDG modalities, the model addresses the computational challenges of 3D images through a 3D-to-2D conversion. Evaluation of the ADNI dataset demonstrates its superiority over baseline models, achieving an accuracy of 0.91 and an area under the curve (AUC) of 0.95. The study emphasizes the effectiveness of ViT in medical imaging, underscores the advantages of multimodal input, and introduces a 3D-to-2D module for streamlined processing in the context of AD diagnosis. Odusami et al. (2023) discuss a pixel-level fusion approach leveraging ViT for early AD. Utilizing multimodal neuroimaging data from MRI and PET, the proposed model employs discrete wavelet transform (DWT) for data fusion and analysis. Transfer learning via a pretrained Visual Geometry Group, has 16 convolutional layers neural network optimizes the DWT technique. Fused images are then classified using a pretrained vision transformer. Evaluation of the ADNI dataset reveals an accuracy of 81.25% for early mild cognitive impairment (EMCI), and late mild cognitive impairment (LMCI) in MRI data and 93.75% for PET data. The ViT model demonstrates superior performance, outperforming existing studies, particularly achieving 93.75% accuracy on PET data. The proposed model offers a promising approach for classifying AD stages, showcasing its potential in real-world applications, and reducing the need for separate models for different imaging modalities. Further research avenues include exploring additional imaging modalities and visualization techniques.

NLP uses ML and linguistic techniques to analyze and understand human language (Zhou et. al., 2019). In AD, NLP extracts meaningful information from medical records, patient interviews, and research papers. It enables automated processing of textual data for tasks such as sentiment analysis, information extraction, and language generation (Bird et al., 2009). The systematic review by Ševčík and Rusko (2022) explores AD detection through speech and NLP, focusing on datasets and participant characteristics. Utilizing databases like Scopus and Web of Science, they analyzed 37 studies from 2019 onward. Prominent datasets included ADReSS, PITT, and CCC, with participant numbers ranging from 30 to 865. While dataset size was a factor, overall quality proved more crucial. Factors like age, gender, and education years emerged as significant indicators for Alzheimer's prediction. The review identifies areas for future research, emphasizing algorithm effectiveness in AD classification and progression prediction. The study by Mirzaei and Adeli (2022) assesses the documentation of cognitive tests and biomarkers in electronic health records (EHRs) for AD and related dementias. Employing a rule-based NLP pipeline, the authors extracted and harmonized cognitive test scores from clinical narratives in a cohort of 48,912 AD/Alzheimer's disease and related dementias (ADRD) patients. Despite low documentation, the NLP pipeline demonstrated accuracy with an *F*1 score of 0.9059. The study highlights the potential of real-world data for AD/ADRD research, emphasizing the need for standardized approaches in EHR documentation for cognitive tests and biomarkers.

ML techniques encompass a broad range of algorithms and methods that enable computers to learn patterns and make predictions from data without being explicitly programmed. These techniques, including decision trees, support vector machines (SVMs), and random forests (RFs), can be applied to various aspects of AD research, such as predicting treatment response, identifying risk factors, and classifying disease subtypes (Hastie et al., 2009). The paper by Mirzaei and Adeli (2022) explores ML techniques for diagnosing AD and related disorders. Various approaches, including

SVM, RF, CNN, and K-means, were covered in the review of articles published since 2016. The study emphasizes the challenge of early AD detection due to the absence of precise biomarkers and the high failure rate in clinical trials. DL techniques, especially CNNs, appear promising, leveraging transfer learning for improved diagnostic accuracy. Ongoing research aims to refine and enhance efficient AD diagnosis and prediction approaches. The paper by Chen et al. (2023) explores the classification of AD using ML techniques. Six algorithms, including KNN, decision tree, rule induction, Naive Bayes, generalized linear model (GLM), and DL, were applied to the ADNI dataset. The GLM achieved an accuracy of 88.24% in classifying AD stages. The study emphasizes the significance of early detection and classification for tailored treatment. Improving healthcare resources, particularly EHRs, can enhance data accessibility. The findings highlight the potential of ML in healthcare for disease detection and diagnosis. Future work could focus on improving classification accuracy, especially for certain AD stages with overlapping attributes.

Predictive modeling involves building mathematical models that predict future outcomes based on historical data. In AD, predictive modeling is utilized to predict the progression of the disease, estimate the probability of developing dementia, or forecast the reaction to a specific treatment. These models leverage ML algorithms to learn from available data and make accurate predictions (James et al., 2021). The study by Moscoso et al. (2019) investigates MRI's efficacy in predicting AD dementia over five years. Key findings include enhanced specificity (71%) and discriminative power (84% AUC) with extended follow-up, challenging the reliance on short-term data for ML algorithms. The research underscores the significance of prolonged follow-up for refining predictive models and ensuring robust performance. Park et al. (2020) present a predictive model for AD, integrating extensive gene expression and DNA methylation data. The research uses a novel feature selection method and deep neural network-based predictive model to address high-dimensional, low-sample-size data issues. Results reveal superior performance to conventional ML algorithms, emphasizing the enhanced accuracy of multi-omics data integration. The proposed methodology holds promise for advancing AD diagnosis and prediction, contributing to understanding the disease's molecular mechanisms.

Data mining and pattern recognition involve extracting valuable insights and identifying patterns from large datasets. In AD, several methods are used to explore different types of data, such as neuroimaging data, genetic information, and clinical records. By doing so, these methods can uncover hidden correlations, biomarkers, and disease patterns. This can help identify the disease early, diagnose it, and design personalized treatment plans (Han et al., 2011). The Buyrukoğlu (2021) study narrates early AD detection using ensemble feature selection approaches and data mining techniques. Focusing on normal, MCI, and AD classes, both homogeneous and heterogeneous ensemble methods are applied. Feature subsets generated through these approaches are utilized in a predictive model employing RF, artificial neural network, logistic regression, SVM, and Naïve Bayes data mining algorithms. Comparative analysis indicates superior performance, with the RF algorithm outperforming, achieving a 91% accuracy when applied to the feature subset obtained through the heterogeneous ensemble feature selection approach. The article by Lazli et al. (2020) investigates computer-aided diagnosis (CAD) systems for brain disorders, notably AD. The CAD system, a synergy of ML and neuroradiology, enables swift diagnoses and emphasizes early AD detection through neuropsychological assessments. By fusing data from various imaging modalities, the CAD system enhances the quality of MRI scans, making them more reliable for clinical use. The article explains the steps involved in CAD, reviews research related to AD, and explores methods for classifying and segmenting brain regions. The article proposes a multimodal fusion approach and conducts a performance study comparing the accuracy of multimodal and single MRI modality CAD systems, focusing on pattern recognition. The discussion highlights the advancements in information fusion in medical imaging and advocates for hybrid models in the diagnosis of brain diseases.

Image analysis techniques involve quantitatively analyzing medical images, such as MRI or PET scans, to assess disease progression in Alzheimer's patients. ML algorithms are applied to extract relevant features, detect abnormalities, track changes in brain structures over time, understand disease progression patterns, and develop effective treatment strategies (Vrooman et al., 2007). Zhang et al. (2021) proposed the Consensus Multi-view Clustering (CMC) model, leveraging non-negative matrix factorization for predicting AD progression stages. CMC integrates multi-view data, automatically learning a unified representation. This novel model mitigates the need for manual parameter settings in multi-view fusion, enhancing clustering accuracy. The study employs brain MRI datasets, utilizing image processing techniques such as SIFT, KAZE, and Gabor filter to create 12 views. Results demonstrate CMC's superior performance over baselines, highlighting its potential for aiding medical diagnosis and detection of AD stages through advanced image processing methodologies. The paper concludes with insights into related work, the proposed model's methodology, optimization algorithms, experimental findings, and future directions. Another study by Ghazi et al. (2019) introduces an innovative long short-term memory (LSTM) algorithm, revolutionizing AD progression modeling by overcoming challenges posed by incomplete data. The proposed LSTM applied to ADNI cohort MRI biomarkers outperforms traditional imputation-dependent methods, significantly reducing mean absolute error. Noteworthy contributions include a novel backpropagation through time formulation, accommodating missing values, and modeling temporal dependencies. With a threefold impact, encompassing multidimensional sequence learning, the paper establishes an end-to-end approach for robust neurodegenerative disease modeling, ensuring LSTM's robustness and statistical significance across diverse scenarios.

Genomic analysis involves studying the genetic makeup of individuals to identify genetic variants associated with AD. ML techniques are used to analyze genomic data, like DNA sequences and gene expression profiles, by employing related genetic markers and pathways. This knowledge can contribute to personalized treatment approaches and drug discovery (Ridge et al., 2013). Li et al.'s (2021) review focuses on AD genomics, spotlighting over 130 susceptible and rare variants linked to APOE, TREM2, CR1, and more. Aging's pivotal role in late-onset AD is explored through somatic mutations in AD patients. The findings underscore innate and adaptive immunity's involvement, emphasizing the systemic failure of cell-mediated amyloid-β clearance in AD progression. Enriching AD-associated variants in myeloid-specific regulatory regions hints at perturbed gene expression affecting Aβ clearance. The emerging paradigm proposes leveraging immunotherapy to boost innate immune functions, potentially modulating AD progression at asymptomatic stages. This genome-wide meta-analysis on AD reveals 29 risk loci and 215 potential causative genes, shedding light on the highly heritable nature of AD. Another study by Jansen et al. (2019), encompassing 71,880 cases and 383,378 controls, emphasizes strong genetic correlations with immune-related tissues and cell types. Implicated genes express prominently in the spleen, liver, and microglia, with identified biological mechanisms involving lipid-related processes and amyloid precursor protein degradation. The findings establish connections with various health-related outcomes and suggest a protective role of cognitive ability against AD risk, advancing our understanding of the genetic factors influencing AD susceptibility.

Data fusion involves integrating and combining heterogeneous data from multiple sources to gain a comprehensive understanding of AD. ML techniques can fuse data from various modalities, such as neuroimaging, genetics, clinical assessments, and lifestyle factors. It can provide a holistic view of the disease and facilitate more accurate diagnosis and treatment decisions (Faisal et al., 2023). This study, by Arco et al. (2021), introduces a novel data fusion system for early AD detection by combining MRI and neuropsychological tests. The model utilizes a Searchlight strategy and SVM classifiers and achieves a maximum accuracy of 80.9%. The Searchlight approach identifies informative brain regions during different stages of the longitudinal study, offering insights into AD development. The system is robust across sessions, avoiding bias from brain atlases, and holds the potential for broader neurological disorder diagnosis. Another study by Abrol et al. (2019) introduces a multimodal data fusion framework, combining deep residual learning of structural MRI (sMRI) features and dynamic functional connectivity (DFC) features from fMRI for predicting AD progression. Cross-validated results reveal a significant performance improvement over unimodal analyses, with p-values of $7.03 \times 10^{\wedge -7}$ for fMRI and $6.72 \times 10^{\wedge -4}$ for sMRI. The study underscores the value of integrating diverse neuroimaging modalities through data fusion, showcasing the efficacy of DL and DFC features in predicting AD progression. The paper by Krokidis et al. (2023) addresses the lack of comprehensive AD single-cell Ribonucleic acid (RNA) sequencing (scRNA-seq) analysis. The proposed computational workflow identifies potential genetic signatures from peripheral blood cells, offering a promising avenue for uncovering blood-based biomarkers and understanding AD pathophysiology at the molecular level.

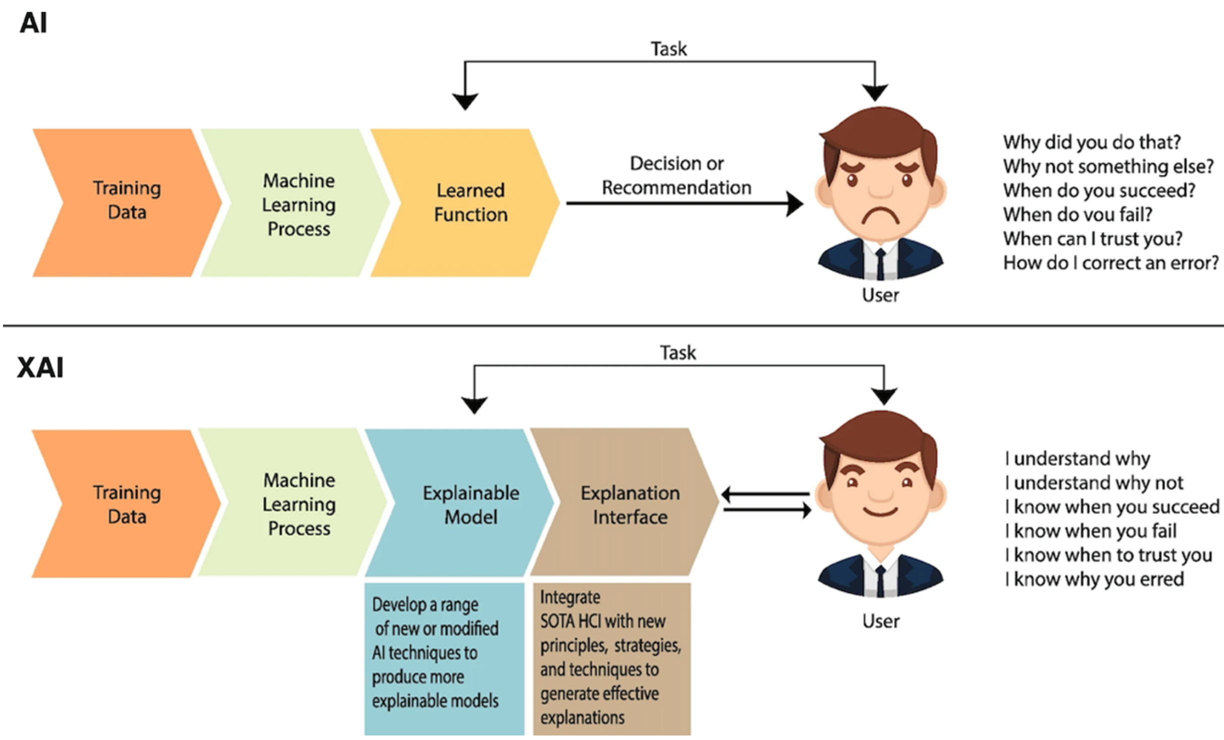
Early detection and diagnosis of AD are crucial for timely intervention and management. ML techniques can be employed to analyze various types of data, such as cognitive assessments, biomarkers, neuroimaging, and genetic information, to develop predictive models that can identify individuals at risk or in the early stages of the disease. Early detection facilitates early intervention and improves patient outcomes (Mormino et al., 2009). Clinical practice in diagnosing early AD emphasizes the importance of early detection for effective management. Alzheimer's progression, from preclinical stages to dementia, necessitates timely identification for planning and lifestyle adjustments. Challenges in early diagnosis include time constraints, diagnostic accuracy, and overlooking symptoms as part of aging. The evolving diagnostic model calls for interdisciplinary care integration, starting with primary care. A review by Porsteinsson et al. (2021) underscores the shift toward early Alzheimer's diagnosis, offering practical guidance and tools for healthcare providers. The multidisciplinary approach ensures timely detection, assessment, and management, aligning with emerging therapeutic prospects for early intervention in AD. In the study by Murugan et al. (2021), the DL Model for Early Diagnosis of Alzheimer's Diseases and Dementia (DEMNET), a CNN, is proposed for efficient classification using MRI images recognizing the crucial stages of AD progression and lack of methods with consistent precision. DEMNET addresses class imbalance issues and outperforms with an accuracy of 95.23%, AUC of 97%, and Cohen's Kappa of 0.93%. Demonstrating robustness, the model achieved an accuracy of 84.83% when tested on ADNI datasets. Future work includes training DEMNET on diverse datasets, utilizing advanced classifiers, and optimizing overall performance.

Digital biomarkers refer to objective and quantifiable measures of physiological, behavioral, or cognitive characteristics collected using digital devices. ML techniques can analyze data from wearables, smartphones, or other digital tools to derive meaningful biomarkers for AD. Digital biomarkers offer the potential for continuous monitoring, early detection, and personalized interventions, by examining early AD manifestations and utilizing biomarkers from sensor and mobile/wearable devices (Kourtis et al., 2019). The article by Kourtis et al. (2019) emphasizes the pivotal role of digital biomarkers amid the escalating healthcare burden of AD. Cognitive, sensory, and motor changes preceding clinical manifestations pose diagnostic challenges, prompting the exploration of consumer-grade mobile and wearable technologies for accessible biomarkers. As AD care costs surge, the urgent development of technologies for early detection and continuous monitoring becomes paramount. Envisaging routine digital phenotyping, potential responses to signal detection, and the establishment of personalized baseline references in clinical trials amplify the significance. The study led by Harms et al. (2022) explores the intersection of digital biomarkers and sex impacts in AD management, emphasizing a potential shift toward innovative medicine. Digital biomarkers, measured by devices, enable high-frequency, longitudinal, and sensitive measurements, particularly in neurodegenerative diseases. The study focuses on sex differences in Altoida's digital medical application, revealing distinct neurocognitive performance signatures between males and females. Notably, these differences may be disease stage dependent. The findings identify the need to integrate digital biomarker technologies into traditional dementia research for precise diagnostics, targeted prevention, and customized AD treatment, considering sex-specific risk profiles and diagnostic tool adjustments.

Explainable AI techniques aim to provide transparent and interpretable models and insights. In the context of AD, Figure 5 (Viswan et al., 2024) implicates how explainable AI methods can help clinicians and researchers understand the underlying factors and features that contribute to disease prediction, treatment response, or diagnostic decisions. Explainable AI helps foster trust in the ML models and enables effective decision-making (Caruana et al., 2015). The article by Viswan et al. (2024) systematically reviews the application of explainable AI (XAI) in AD classification. Acknowledging the limited acceptance of AI models in medical diagnosis due to their black-box nature, the study focuses on XAI methods employed in AD prediction over the past decade. Following Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, the review categorizes AI models based on various XAI methods and frameworks, providing a comprehensive spectrum from intrinsic to complex interpretations. The study evaluates the merits of different interpretation forms, offering profound insights into factors supporting clinical AD diagnosis while addressing limitations and outlining open research challenges.

Another article by Sudar et al. (2022) explores AD identification through XAI using Layer-wise Relevance Propagation (LRP), VGG-16, and CNN. The study employs an Alzheimer's brain image dataset and XAI for trustworthy results. LRP, VGG-16, and CNN contribute to accurate predictions and feature explanations. Combining XAI and neural networks provides a trustworthy solution for Alzheimer's diagnosis. The study's transparency enhances interpretability, offering insights into the decision-making process. The paper by Holzinger et al. (2022) highlights the significant role of conceptual knowledge in advancing robust and explainable medical AI. The paper integrates three research areas, namely, complex networks, graph causal models, and verification and explainability, to unify research and practical applications. The paper

Figure 5
A typical difference between AI and XAI where a health worker gains trust with XAI



also emphasizes the importance of ethical and legal considerations for trustworthy medical AI solutions.

These techniques show a wide range of applications in AD intervention, including DL, ViT, NLP, and ML. They hold great potential for improving diagnosis, treatment, and care for individuals with Alzheimer's and advancing our understanding of this complex neurodegenerative disease.

Table 3 compares various DL, ViT, NLP, and ML techniques. It highlights their respective techniques, benefits, challenges, and references for further exploration. The table provides a concise overview of these techniques and their relevance in the context of AD interventions.

Table 4 represents the usage ratio of various techniques in the field of DL, ViT, NLP, and ML among different age groups (50–60, 60–70, and 70–80 years). The usage ratio indicates the extent to which each technique is employed within each age group. Note that the usage ratios in the table are hypothetical and serve as an example. The actual usage ratios may vary depending on factors such as technological advancements, accessibility, and specific research or industry contexts. Figure 6 shows the pictorial representation of Table 4. The usage ratio is represented as a decimal number ranging from 0 to 1, where 1 signifies a high adoption rate and 0 indicates a low adoption rate. For example, in the age group 50–60 years, the technique "DL" has a usage ratio of 0.6, implying that it is relatively more widely used in this age group compared to others. Similarly, the usage ratios for other techniques can be observed for each age group.

5. Findings and Discussion

From the results presented in the table, we can observe the utilization of both conventional intervention techniques and advanced technologies such as DL, ViT, NLP, and ML in AD intervention.

Conventional intervention techniques such as cognitive stimulation, RO, validation therapy, RT, assistive technologies, electronic memory aids, communication apps and devices, GPS tracking devices, and AAL are still widely used in managing and supporting AD. These techniques provide various benefits, such as cognitive enhancement, improved communication, increased independence, and better quality of life for individuals with Alzheimer's. However, they may also present challenges related to implementation, caregiver training, and individual responsiveness.

On the other hand, these advanced technologies offer promising avenues for AD intervention. For instance, DL techniques can analyze complex patterns and structures in data, enabling the development of predictive models and personalized treatment approaches. ViTs enable efficient and accurate analysis of medical images, facilitating image analysis for disease progression and CAD. NLP techniques aid in understanding and extracting information from medical records, enabling disease subtyping and NLP for medical applications. Also, ML techniques, including predictive modeling and data mining, allow for identifying predictive biomarkers and discovering potential drug targets.

These advanced technologies provide benefits such as improved diagnosis accuracy, personalized treatment strategies, early detection, and longitudinal disease modeling. However, they also come with challenges related to data privacy and security, interpretability of AI models, patient acceptance and trust, integration with existing healthcare systems, technical challenges, regularity compliance, ethical considerations, interoperability, and workforce training and education, as shown in Figure 7.

When comparing the traditional techniques for intervening in AD, such as cognitive stimulation and caregiver support, with innovative methods, such as DL and NLP, traditional approaches emphasize cognitive enhancement and social interaction but come

Table 3
Cutting-edge Alzheimer's disease intervention techniques

#	Name	Techniques	Benefits	Challenges	Reference
1	Deep learning	Neural networks with multiple layers	Accuracy prediction and automatic feature learning for early detection	Large data requirements, computationally intensive, black-box nature	Zhao et al. (2023)
2	Vision transformers	Attention-based transformer architecture for image processing	Effective in image recognition, attention mechanism for capturing global and local context	Limited interpretability, high computational cost, challenges in handling large images	Dosovitskiy et al. (2020)
4	ML techniques	Various algorithms for pattern recognition and prediction	Versatile in different domains, automated decision-making, pattern discovery	Feature engineering, overfitting, bias in training data	Hastie et al. (2009)
5	Predictive modeling	Statistical modeling and algorithms for prediction	The potential of translating predictive models into practical clinical applications through user research, adoption opportunities, and the conceptual design of a decision support tool, fostering more effective disease management	Overfitting, model complexity, selection bias, data quality, and preprocessing	Bellio (2021)
6	Data mining and pattern recognition	Extracting knowledge from large datasets	Discover hidden patterns, identify associations, extract useful information	Data preprocessing, scalability, interpretability	Han et al. (2011)
7	Image analysis for disease progression	Analyzing medical images to track disease progression	Early detection, quantitative assessment, treatment monitoring	Image variability, accuracy and reproducibility, data preprocessing	Chen et al. (2019)
8	Genomic analysis	Analyzing genomic data for insights into disease mechanisms	Identification of genetic markers, personalized medicine, understanding disease pathways	Data integration, interpretation of complex data, ethical considerations	Visscher et al. (2007)
9	Data fusion	Integrating information from multiple sources	Data fusion in computational analysis promises to identify potential biomarkers for Alzheimer's disease, offering insights into diagnostic and therapeutic advancements	Data compatibility, integration methods, data quality and reliability	Krokidis et al. (2023)
10	Early detection and diagnosis	Identifying diseases at early stages	Early intervention, improved prognosis, better treatment outcomes	Sensitivity and specificity, false positives, access to early screening	Sardanelli and Di Leo (2012)
11	Digital biomarkers	Utilizing digital data to monitor health indicators	Non-invasive monitoring, real-time data collection, remote patient management	Data validity and reliability, regulatory considerations	Chan et al. (2019)
12	Explainable AI	Interpreting and explaining AI model predictions	Fostering robust, explainable, and trustworthy outcomes in the realm of medical artificial intelligence	Complexity of models, trade-off between interpretability and performance	Holzinger et al. (2022)

Note: ML, machine learning; AI, artificial intelligence

with challenges, such as limited long-term effectiveness and the need for trained facilitators. On the other hand, advanced technologies offer benefits such as improved diagnostic accuracy and personalized treatment strategies, but they face obstacles such as data privacy concerns and interpretability issues. By combining these approaches, we can achieve synergistic effects, addressing the limitations of each method. By examining this interplay, we can gain a more comprehensive understanding of AD intervention, which can inform future research to optimize techniques and develop personalized intervention strategies.

Integrating AI into AD interventions has raised several ethical concerns. The issues related to data privacy, algorithmic bias, and informed consent are crucial. Protecting patient data, mitigating bias, and ensuring transparent consent processes are essential. Healthcare professionals must navigate accountability while preserving the patient–provider relationship. Therefore, balancing AI's autonomy with human judgment is critical to ensuring ethical AD care.

6. Future Research

Future research in AD intervention techniques holds promise in several key areas. Long-term effectiveness and personalized response evaluation are crucial for understanding the impact of interventions on cognitive function and daily life. Interdisciplinary collaboration is essential for optimizing techniques and fostering communication networks.

Remote monitoring using AI offers the potential for real-time assessment, while personalized intervention strategies driven by

Table 4
Hypothetical representation of the usage ratios for each intervention technique across different age groups (50–60, 60–70, and 70–80 years)

#	Technique	Usage ratio (50–60 years)	Usage ratio (60–70 years)	Usage ratio (70–80 years)
1	Deep learning	0.6	0.5	0.4
2	Vision transformers	0.3	0.2	0.1
3	Natural language processing	0.7	0.6	0.5
4	ML techniques	0.8	0.7	0.6
5	Predictive modeling	0.4	0.3	0.2
6	Data mining and pattern recognition	0.5	0.4	0.3
7	Image analysis for disease progression	0.3	0.2	0.1
8	Genomic analysis	0.5	0.4	0.3
9	Data fusion	0.4	0.3	0.2
10	Early detection and diagnosis	0.6	0.5	0.4
11	Digital biomarkers	0.6	0.5	0.4
12	Explainable AI	0.4	0.3	0.2

Note: ML, machine learning; AI, artificial intelligence

Figure 6
Cutting-edge intervention techniques usage ratio across age groups

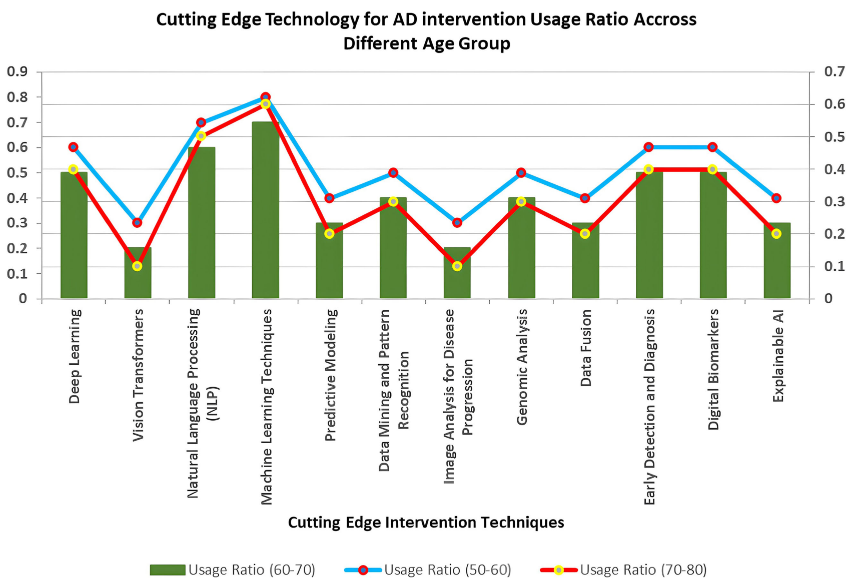
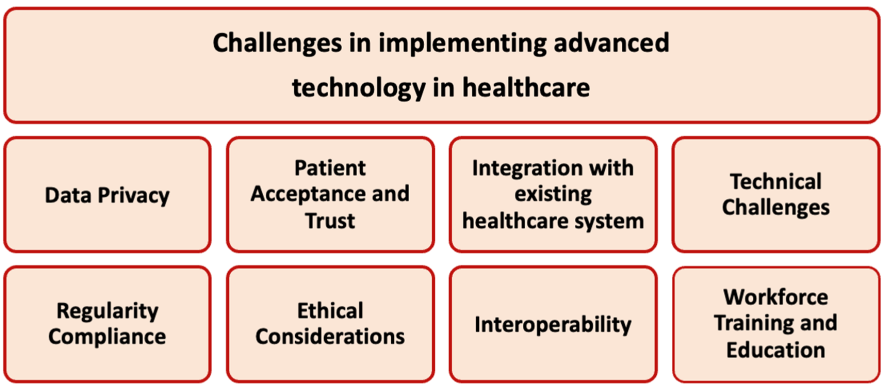


Figure 7
Challenges in implementing advanced technology in healthcare



adaptive algorithms could greatly enhance treatment outcomes. Integrating multimodal data sources, usability testing, and user-centered design are crucial for accessibility and effectiveness, along with cost-effectiveness and scalability evaluations to understand resource implications.

Integrating technology with traditional therapies, optimizing multisensory stimulation, and enhancing caregiver support are pivotal for improving the quality of life. Advanced fusion techniques for data integration, incorporating ambient intelligence and IoT, and addressing ethical and legal considerations are essential.

Conducting real-world validation and longitudinal studies is crucial to evaluating a treatment or intervention's clinical usefulness and long-term effectiveness. Combining conventional intervention techniques and cutting-edge advanced technologies can significantly enhance AD intervention and support. It allows for a multidimensional approach that addresses the disease's cognitive, functional, and behavioral aspects while leveraging the power of data analysis and technological advancements.

Future research and development in these areas promise to improve the quality of care and outcomes for individuals affected by AD.

7. Conclusion

The paper compares the conventional techniques used for AD intervention with advanced technologies like DL and NLP. While conventional methods offer benefits such as cognitive enhancement, they face challenges in implementation and caregiver training. Advanced technologies promise personalized treatment but encounter issues like data privacy and interpretability. Integrating these approaches can address their limitations and provide a more comprehensive AD intervention strategy. However, ethical concerns arise with AI integration. Balancing these techniques can optimize AD care and improve outcomes for affected individuals.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

Noushath Shaffi is the Associate Editor for *Artificial Intelligence and Applications*, and was not involved in the editorial review or the decision to publish this article. The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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