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Artificial Intelligence in Dementia Care: From Diagnostic Tools to Daily Living Assistance

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Abstract: The goal of the present article is to provide a systematic analysis of all recent developments in Artificial Intelligence-based (AI) systems developed for the diagnosis and treatment of dementia. These AI-based systems are designed to support early detection, continuous assessment, and social support for dementia patients. While much attention has focused on using AI to detect and assess various forms of dementia, few researchers have examined how these AI-based systems can be used as part of a complete care process for people with dementia. Therefore, this study provides a detailed description of using AI as part of a complete care system for people with dementia. The methodological approach employed includes a clear definition of the selection criteria for articles included in the review. The results identify many ongoing challenges, limitations, and research needs related to using AI as part of a complete care system for people with dementia.

Keywords: Artificial intelligence; dementia care; machine learning; cognitive assessment; assistive technologies

1. Introduction

Dementia is a type of progressive neurodegeneration that substantially interferes with memory, thinking, and daily life. The World Health Organization (2021) reports that there are now 55 million people worldwide diagnosed with dementia, with almost 10 million diagnosed each year. Alzheimer's disease is the most prevalent type; however, other dementias, such as vascular and Lewy body dementia, are not infrequent and add significant societal burden. The growing prevalence of dementia has serious ramifications not only for those living with dementia but also for families, caregivers, and the entire health care organization system [1]. The disease often creates a loss of independence for the patient, emotional stressors for the family, and added health care costs, marking dementia as a significant global public health issue.

Dementia care also faces real challenges. Even with advances in clinical research, diagnosis can take years. The early-stage symptoms can often look so benign as to suggest it's normal aging, or cognitively not appear to be related to dementia at all (with no temporal association). Even when dementia is identified, cognitive decline will often have advanced to a moderate to severe level. The ability to participate in a treatment or intervention is reduced. Further differentiation of care also reveals legitimate issues in the patient care workforce, and the care model imposes physical, emotional, and financial hardship on families. And from the patient perspective, there remain hurdles, where issues (ie.,

loss of agency, social isolation, health and well-being, etc.) remain [2]. These challenges suggest a need to redesign early diagnosis and appropriate daily living activity supports.

Artificial intelligence (AI) is being heralded as a disruptive technology in dementia research and care. AI systems can process large-scale datasets—brain imaging data, genetic sequences, vocalizations, and behavioral cues—beyond human capacity. Deep learning methods used to analyze MRI and PET scans can identify structural and functional changes in the brain earlier than previous diagnostic tools. Natural language processing can detect subtle, often intermittent differences in speech and language, providing early warnings of cognitive decline [3]. Wearable sensors and smart home devices can provide information through continuous monitoring in the home, while robotics and conversational AI provide automated companionship, reminders, and assistance with activities of daily living. These innovations suggest that AI cannot only improve diagnosis but also improve patients' quality of life and reduce the burden on caregivers.[4]

2. Background

2.1 Overall System Architecture Overview of Dementia and Related Disorders

Dementia is a term that covers a group of symptoms related to the progressive decline of cognitive functions, including memory, reasoning, communication, and problem-solving. The most common form is Alzheimer's disease (AD), which comprises 60–70% of cases, while vascular dementia, dementia with Lewy bodies, and frontotemporal dementia are also subtypes. Each subtype has its own pathological features, for example, amyloid-beta plaques and tau tangle pathology in AD and vascular damage in vascular dementia [5]. Although there are differences, clinical presentations can overlap, making accurate diagnosis difficult. Dementia classes progress from mild cognitive impairment in early stages to moderate impairment with dependence, and in advanced stages, complete dependence that requires constant care.

2.2 Current Non-AI Diagnostic Practices

Traditional diagnosis for dementia relies on a combination of clinical assessment, neuropsychological testing, and brain imaging. Testing instruments like the Mini-Mental State Exam (MMSE) or the Montreal Cognitive Assessment (MoCA) are generally used to assess cognitive functions such as learning, memory, attention, and reasoning. Structural MRIs and PET scans identify structural changes and, in the case of PET scans, amyloid or tau pathology [6]. Biomarker analysis or analysis of cerebrospinal fluid (CSF) samples provides further assurance of a suboptimal "at-risk" disease state. While these are the clinical "gold-standard," they are expensive, invasive, and sometimes inefficient (e.g., too little, too late) for treatment in the early-mild stage of the disease [7].

2.3 The Current Care Landscape

Beyond diagnosing the dementia, dementia care is also heavily dependent on the formal and informal care providers. In general, families end up being the key care provider. This includes providing a significant emotional, physical, and financial burden. Formal care systems, such as memory clinics, nursing homes, and assisted living, provide more consistent support. But costs and limited availability of trained professionals limit them [8]. Technologies like reminders to take medications, safety alarms, and mobility devices help eliminate some burden of care, but these mechanisms provide a task-driven utility that does not account for the dynamic and shifting needs of individuals living with dementia. Other therapies, such as occupational therapy, cognitive training, or psychosocial support services, exist to provide some positive mood, mobility, or confidence benefits. But once again, they do not address the scale of need.

2.4 Purpose of the Background Section

This part provides a foundation for understanding how Artificial Intelligence can complement or, in some instances, transform dementia care. By outlining current diagnostic and caregiving methods, it highlights gaps and shortcomings in current care practices that AI technologies aim to address. The next sections describe how AI-based techniques will be involved in diagnostic processes and in assisting with daily living to increase precision, efficiency, and quality of life.

3. Review Methodology

This study utilizes a structured narrative review methodology to assess how Artificial Intelligence (AI) has impacted dementia care. Aspects covered include early diagnosis, daily living assistance, and related areas. This review aims to synthesize current research, identify technological improvements, and provide an overview of knowledge gaps across different levels of dementia care. Using appropriate keywords combined with Boolean operators such as "AND" and "OR", a thorough literature search was performed. Keywords searched included, but were not limited to, "Artificial Intelligence in dementia care," "AI-based diagnosis of dementia," "machine learning in Alzheimer's detection," "assistive technologies for dementia patients," and "AI in daily living assistance." Each keyword was searched alone and in combination to capture a wide range of pertinent literature. Studies were collected from reputable online academic databases that are known to be interdisciplinary in nature. Databases include IEEE Xplore, Scopus, Web of Science, SpringerLink, and Google Scholar. Using these databases ensured that we captured interdisciplinary research related to artificial intelligence, health care, and assistive technologies. Inclusion/exclusion criteria were established prior to selecting the studies. Inclusion criteria included studies published in peer-reviewed journals or conference proceedings that used AI or machine learning to diagnose or support the care of individuals with dementia and were written in English. In addition, studies that did not focus specifically on dementia, were duplicates, were insufficiently detailed regarding methods, or were non-scholarly (e.g., editorials, blog entries) were excluded. Only studies published between 2015 – 2025 were evaluated due to the rapid development of AI-based technologies applicable to healthcare and assistive systems during this time frame. Multiple stages occurred during the article selection process. We initially identified approximately 100 articles through database searches. Duplicate articles were removed, leaving 80 articles, which were then narrowed to 70 by screening titles and/or abstracts. The remaining 60 articles then underwent full-text review. Finally, after careful assessment, 40 – 50 studies were ultimately selected to be included in the final analysis based upon their relevance and contributions to AI-based dementia care. Principles derived from the PRISMA framework were followed throughout the review process to ensure the greatest level of transparency and reproducibility possible. A qualitative analysis of each of the selected studies was also completed based upon several factors including: Type(s) of AI techniques used within each study, Application domain(s) (i.e. diagnosis, daily assistance etc.), Dataset(s) used, Performance metric(s) presented, and Reported limitation(s). Furthermore, the quality of each selected study was evaluated based on several factors, including methodological rigor, Relevance to dementia care, Validation technique(s) used, and practicality in applying findings to real-world settings.

4. Literature Review

Recent advances in early dementia detection have been substantial, and more recently, AI, machine learning, and other allied technologies have become increasingly integrated. The most recent work of Steijger et al. [9] (2025) stated that projects in AI aimed at improving the quality of the facilities for persons with dementia are at the feasibility stage rather than the experimentation stage, and they need verification on a large scale in the real world before they can be proved to be useful in applied clinical situations. Shi and Zhou et al.[10] (2025) investigated the caregiver perceptions of socially assistive robots and found generally good impressions, and that such robots could overcome disabling negative attitudes and lower the burden of care upon caregivers, and the rate of the progression of the disease. Tree and Jones et al. [11] examined face recognition problems among subjects self-referred with developmental prosopagnosia (DP) to assess their awareness of their facial recognition ability. In a 2024 study, Arco et al. [12] used ECG-derived heart rate variability (HRV) features to classify cognitive decline, offering a cost-effective alternative to brain imaging. Chakraborty et al. [13] used data from the OASIS and ADNI databases to achieve high classification accuracy in detecting Alzheimer's using Light Gradient Boosting Machine (LGBM) and Multilayer Perceptron (MLP) supervised machine learning models. Biswas et al. [14] reviewed Explainable AI (XAI) to support transparent decision-making in the formal diagnosis of dementia, raising relevant questions about bias and privacy. Yeasmin et al. [15] attempted to use CAD (Computer-Aided Diagnosis) with AI (Artificial Intelligence) to deliver a real-time, remote, personalized diagnosis. Yadollahikhales et al. [16] studied the ability to see faces early in Septo-Temporal Dementia (SD), before pronounced semantic deficits occurred. Mohammed et al.

conducted a comparative study of the various deep learning methodologies for detecting Alzheimer's, particularly in terms of the imaging and preprocessing undertaken. In the year 2023, abnormal behavior patterns were found in dementia patients by Kim et al. [17] using inexpensive sensors and a multilayer perceptron model. Alsubai et al. [18] achieved 95% accuracy for early detection using machine learning classifiers, finding that a multilayer perceptron outperformed decision trees, naïve Bayes, and SVM. Zheg et al. showed the potential of face-feature-related features to detect dementia using the PROMPT dataset-based interviews. Kantayeva et al. [19] surveyed machine learning methods used for dementia diagnosis, showing that the method has a promising future. It also examined cognitive, movement, speech, and imaging tests based on artificial intelligence for more cost-effective and accurate dementia detection. It is predicted that the global number of dementia patients will rise exponentially to approximately 152.8 million by 2050 as a result of increased risk from all causes and accelerated aging in the population. Chimamiwa et al. criticized tools developed using smart home technology for use with dementia patients and analyzed the requirements for detecting lateralization and activities.

In 2021, Juneja et al. [20] studied IoMT-based sensor systems for early dementia diagnosis and patient care. Garcia-Constantino et al. developed the SHIB (Smart Home in a Box) system to monitor the welfare of patients in care facilities. Previously, in 2020, Thabtah et al. assessed dementia screening methodologies, mapped them to cognitive domains, and reported encouraging results on websites using machine learning techniques, such as ACE-Mobile. Oaishi et al. [21] examined recognition errors in patients with DLB and AD, looking at object recognition from a variety of angles and with different textural backdrops. Significant changes in recognition were noted, particularly when the views were noncanonical and blurry.

Hayhurst [22] examined the use of augmented and virtual reality as cognitive aids to individuals with dementia. Their findings identified advantages and design difficulties. Boumpa et al. [23] described a smart home system that used sound signals as a memory aid. Chandra et al. [24] investigated face recognition problems noted in bvFTD, finding greater susceptibility to prosopagnosia in females. Amiribesheli and Bouchachia [25] developed dementia-assisting smart home systems validated by caregivers. They identified cognitive and perceptual characteristics of SD and DP patients. They developed an RGBD camera fall-detection system as part of an activity-recognition control framework that included privacy protection.

Table 1. Comparative Analysis of AI Approaches in Dementia Care

Sr. No	Article Title	Author/ Ref No.	Year	Technique Adopted	Strength and Limitation of Approach
1	Using shallow neural networks with functional connectivity from EEG signals for early diagnosis of Alzheimer's and frontotemporal dementia	Ajra et al. / [1]	2023	Shallow Neural Networks (EEG-based)	**Strength:** Non-invasive, effective for early diagnosis using EEG signals. **Limitation:** Lower accuracy compared to deep learning; sensitive to noise in EEG data.
2	Artificial intelligence for diagnostic and prognostic neuroimaging in dementia: A systematic review	Borchert et al./[2]	2023	AI-based Neuroimaging (ML/DL)	**Strength:** Comprehensive diagnostic insights using imaging biomarkers. **Limitation:** High computational cost; requires large annotated datasets.
3	Harnessing artificial intelligence for transforming dementia care: Innovations in early detection and treatment	Habbal et al./[4]	2025	AI-based Integrated Models	**Strength:** Covers end-to-end dementia care (diagnosis to treatment). **Limitation:** Limited real-world validation and deployment.
4	Social and Assistive Robotics in Dementia Care	Ienca et al./[5]	2016	Assistive Robotics	**Strength:** Enhances patient interaction and emotional support; limitation: ethical concerns and high implementation cost.
5	Intelligent dementia-friendly living space integrating robotics and sensors	Khan et al./ [6]	2024	IoT + Robotics + Spatial AI	**Strength:** Real-time monitoring and adaptive environment. **Limitation:** Privacy issues; system complexity.
6	Technology that CARES: Enhancing dementia care through assistive technologies	Kiselica et al./[7]	2024	Assistive Technologies	**Strength:** Improves quality of life and independence. **Limitation:** Usability challenges for elderly users.
7	Dementia assessment using Mandarin speech with attention-based encoder	Lin et al./[8]	2023	NLP + Speech Recognition	**Strength:** Non-invasive cognitive assessment using speech. **Limitation:** Language dependency; limited generalization.
8	Use of AI to support quality of life of people with dementia	Steijger et al./[9]	2025	AI-based Assistive Systems	**Strength:** Focus on quality-of-life improvement—**limitation:** Lack of standardized evaluation metrics.

Table 1. Comparative Analysis of AI Approaches in Dementia Care (continue)

Sr. No	Article Title	Author/ Ref No.	Year	Technique Adopted	Strength and Limitation of Approach
9	Identifying HRV patterns in ECG signals as early markers of dementia	Arco et al./[12]	2023	ML on ECG/HRV Signals	**Strength:** Early detection using physiological signals. **Limitation:** Requires medical-grade data collection.
10	ANALYZE-AD: Comparative analysis of AI approaches for Alzheimer's detection	Chakraborty et al./[13]	2024	Comparative ML/DL Models	**Strength:** Benchmarking of multiple AI models. **Limitation:** Limited dataset diversity.
11	Detecting abnormal behaviors using lifelog data	Kim et al./[17]	2023	Machine Learning + Lifelog Data	**Strength:** Continuous monitoring of patient behavior. **Limitation:** Privacy concerns and data reliability issues.
12	Automated cognitive health assessment based on daily activities	Alsubai et al./[18]	2023	ML-based Activity Recognition	**Strength:** Real-time assessment using daily activities. **Limitation:** Depends on accurate sensor data.
13	IoMT-based early detection and care of dementia	Juneja et al./[20]	2021	IoMT + AI	**Strength:** Remote monitoring and healthcare integration. **Limitation:** Security and interoperability challenges.
14	Acoustic-based smart home system for dementia patients	Boumpa et al./[23]	2019	Smart Home + Audio AI	**Strength:** Non-intrusive monitoring system. **Limitation:** Limited contextual understanding.
15	Socially assistive robots for dementia care (meta-analysis)	Yu et al./[26]	2022	Social Robotics	**Strength:** Improves cognition and emotional well-being. **Limitation:** Limited long-term effectiveness studies.
16	3D Transformer for differential diagnosis	Nguyen et al./[27]	2023	Transformer-based Deep Learning	**Strength:** High accuracy in complex imaging tasks. **Limitation:** Computationally expensive and data-hungry.
17	ADMarker: Multimodal federated learning system	Ouyang et al./[28]	2024	Federated Learning + Multimodal AI	**Strength:** Privacy-preserving and multi-source data integration. **Limitation:** Complex implementation and communication overhead.
18	AI as a tool for cognitive impairment screening: Patient perspectives	Wurtz et al./[32]	2025	AI Screening Tools	**Strength:** User-centric insights and acceptability. **Limitation:** Limited technical evaluation.

Table 1. Comparative Analysis of AI Approaches in Dementia Care (continue)

Sr. No	Article Title	Author/ Ref No.	Year	Technique Adopted	Strength and Limitation of Approach
19	Reinforcement learning for adaptive robotic assistance	Yuan et al./[33]	2025	Reinforcement Learning + Robotics	**Strength:** Personalized and adaptive care. **Limitation:** Requires extensive training and real-world validation.
20	Smart home in a box for dementia monitoring.	García-Ceja et al./[46]	2021	Smart Home + IoT + AI	**Strength:** Scalable and modular monitoring system. **Limitation:** Installation and maintenance complexity.

The comparative evaluation in Table 1 shows that machine learning based on large amounts of data (deep learning) generally performs better at diagnosing neurological conditions using imaging data than traditional methods, with CNNs and transformers particularly well suited to this task. However, these methods typically require significantly more computing resources, and the results can be difficult to interpret. In contrast, many forms of machine learning, when used with physiological or behavioral data, are much easier to understand and require less computing power. As a result, they may be more likely to be implemented and evaluated in a clinical setting. Smart home devices, wearable technology, and social robots are assistive technologies that can support patients with Alzheimer's disease by improving their overall quality of life. Despite their potential benefits, several barriers remain to implementing these interventions across a wide range of settings, including privacy, usability, and scalability. Recent research has shown that emerging methodologies, including federated learning and reinforcement learning, may create individualized and private care strategies for individuals with dementia.

5. Artificial Intelligence in Dementia Detection and Diagnosis

5.1 AI in Neuroimaging-Based Diagnosis

Medical imaging is one of the most advanced areas for using AI in dementia detection. Specifically, deep learning (e.g., convolutional neural networks, CNNs) has proven highly effective in analyzing MRI, CT, and PET imaging data to identify subtle brain changes that human radiologists may miss. For instance, AI models can detect hippocampal atrophy, cortical thinning, and white matter hyperintensities as early pathology markers for Alzheimer's disease and vascular dementia [26]. Compared with traditional manual interpretation, AI systems process large volumes of image data quickly and automatically categorize patients into diagnostic groups (e.g., "healthy control," "mild cognitive impairment (MCI)," or "dementia"). Additionally, predictive models trained on longitudinal imaging data can predict disease development and provide clinicians with relevant prognostic information.

5.2 AI in Cognitive and Behavioral Assessment

Artificial intelligence (AI) has become a way to assess cognition and behavior that is continuous, objective, and data-driven. AI capabilities in machine learning, computer vision, and pattern recognition have been applied in many ways to analyze behavioral indicators (e.g., eye contact), facial expressions, speech patterns, and interaction history to identify early warning signs of cognitive decline and track disease progression. For example, an AI system using identity assistive technologies could determine whether cognitive issues were present through measures such as how often a patient could not recognize their own face, how long it took them to respond to questions, and whether they relied heavily on assistance. Additionally, the patient's emotional state, including confusion and engagement, would provide evidence of behavioral problems [27]. This information provides the basis upon which an AI system will adjust the amount and type of support offered to each individual with dementia. Finally, when caregivers' observations are integrated into the assessment process, these assessments can better reflect individual needs and more effectively support people with dementia.

5.3 AI in Biomarker-Based Diagnosis

Biomarker-based dementia diagnosis relies on well-established knowledge of amyloid-beta, tau, and neurofilament light chain (NfL). AI enhances biomarker-based diagnosis by performing exhaustive analyses of continually evolving multimodal datasets (e.g., genomics, proteomics, and metabolomics). Machine learning models ultimately use biomedical marker profiles and apply them to clinical and imaging data for better diagnostic specificity. For classifying Alzheimer's disease subtypes using heterogeneous biomarker datasets, researchers have used ensemble learning techniques [28]. Additionally, AI is particularly useful for identifying discriminatory marker signatures that traditional statistical analysis may miss, which may drive early-stage screening and personalized therapy.

5.4 Strengths and Limitations of AI in Diagnosis

AI-based diagnostic systems offer considerable advantages, such as high accuracy, scalability to tens of millions of patients, and, in some cases, earlier diagnoses. Additionally, automating analytics could help inform clinical triage pathways, while alleviating clinician burden and improving reproducibility and standardization (i.e., reducing the chance of human error and inter-observer variability). Moreover, AI systems that can leverage multimodal data sources will likely provide the broadest understanding of disease progression [29]. There are limitations, however. Many AI algorithms have been developed using slightly curated, relatively small, or homogeneous data sets, raising questions about their validity in other populations. In addition, the 'black box' nature of deep learning algorithms poses a challenge for clinical implementation, as end users (i.e., health care providers) need interpretability and explainability to trust and act on algorithmic recommendations [30]. Finally, integrating AI into health systems brings up ethical, legal (i.e., patient privacy, data governance), and practical (i.e., cost and utility) questions.

6. AI for Daily Living Assistance in Dementia Care

6.1 Assistive Robotics

Robotics is a leading application area of Artificial Intelligence in dementia care. Certain socially assistive robots (ie, PARO, the therapeutic robot seal, and humanoid robots such as Pepper) have been designed to deliver companionship, emotional comfort, and cognitive stimulation to individuals with dementia [31]. They employ AI-driven speech recognition, emotion detection, and learning algorithms to engage customers in a personalized, prescriptive way. Studies indicate that spending time with robots decreases agitation, loneliness, and stress, and increases engagement in therapy-related tasks. Beyond companionship, service robots are being developed to assist with self-care activities, such as reminding patients to take medication, assisting with mobility, and monitoring for safety to reduce caregiver stress.

6.2 Smart Homes and Ambient Assisted Living (AAL)

Smart home technology uses the synergistic capacity of AI and IoT to create flexible environments that enable safe, independent living. Smart home environments use embedded sensors to track patient movement, sleep patterns, and behaviors like stove misuse or going out of the house at night. Machine learning algorithms can use sensor data to detect deviations from baseline or normal behavior and trigger alerts to caregivers. Fall detection systems use AI to differentiate between non-harmful and harmful events, so alerts are sent to the caregiver promptly when your elder falls [32]. In general, smart home technologies can provide automatic reminders for things like eating, hydration, and medication adherence, which are critical, in particular, to dementia care.

6.3 Conversational Agents and Virtual Assistants

AI-driven conversational agents built with NLP offer an inexpensive way for patients to receive cognitive and emotional support. Virtual assistants like Apple Siri, Amazon Alexa, or dementia-care chatbots provide patients with communication, engagement, or reminders about daily activities, and can repeat the same questions or responses without the nuisance or frustration. More advanced bots may even include emotion recognition to provide responses based on emotions [33]. Conversations can provide emotional stimulation while lessening the burden on caregivers to provide repetitive communication or reminders. Conversational agents may also be incorporated as cognitive training applications, as they can engage patients in memory, storytelling, and question-and-answer exercises. Figure 1 represents the organization and flow chart of the IoT sensor-based system for caring for dementia patients.

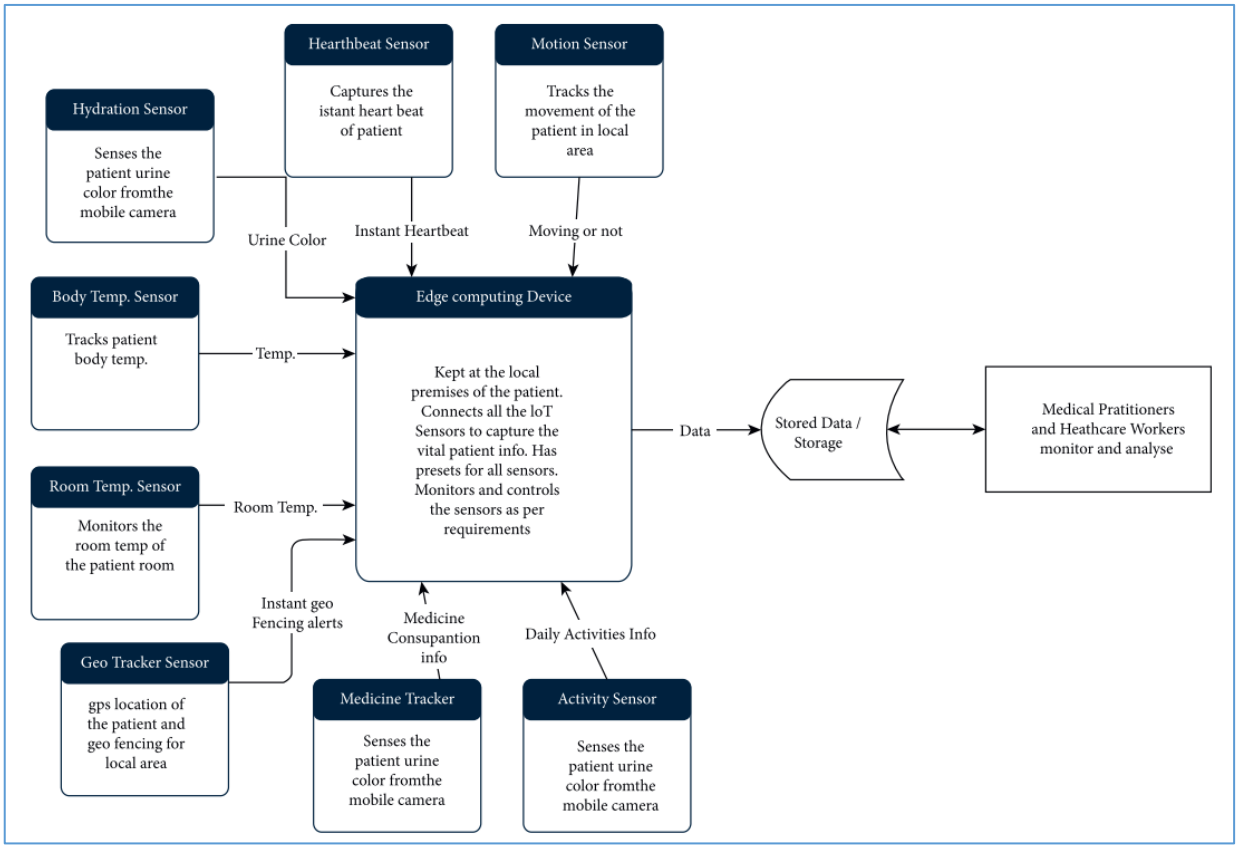


Figure 1. represents the flow chart of the IoT-based system for care of dementia Patients [20]. (Open Access)

6.4 Wearable Technologies for Daily Assistance

Wearable technology - e.g., AI-enabled smartwatches and fitness bands - adds to the growing prominence of health monitoring, offering real-time support. They track heart rate, sleep quality, activity levels, and use GPS-enabled software to minimize wandering [34]. AI-enabled wearables can provide tailored feedback, such as detecting combinations of fatigue and providing advice and rest, and alerting a care partner when unusual patterns emerge. Some wearable technology systems also integrate voice-activated assistants so users can ask for support, reminders, or help navigating an experience. Figure 2 represents a machine learning system using wearable technologies to track abnormal behavior in dementia patients.

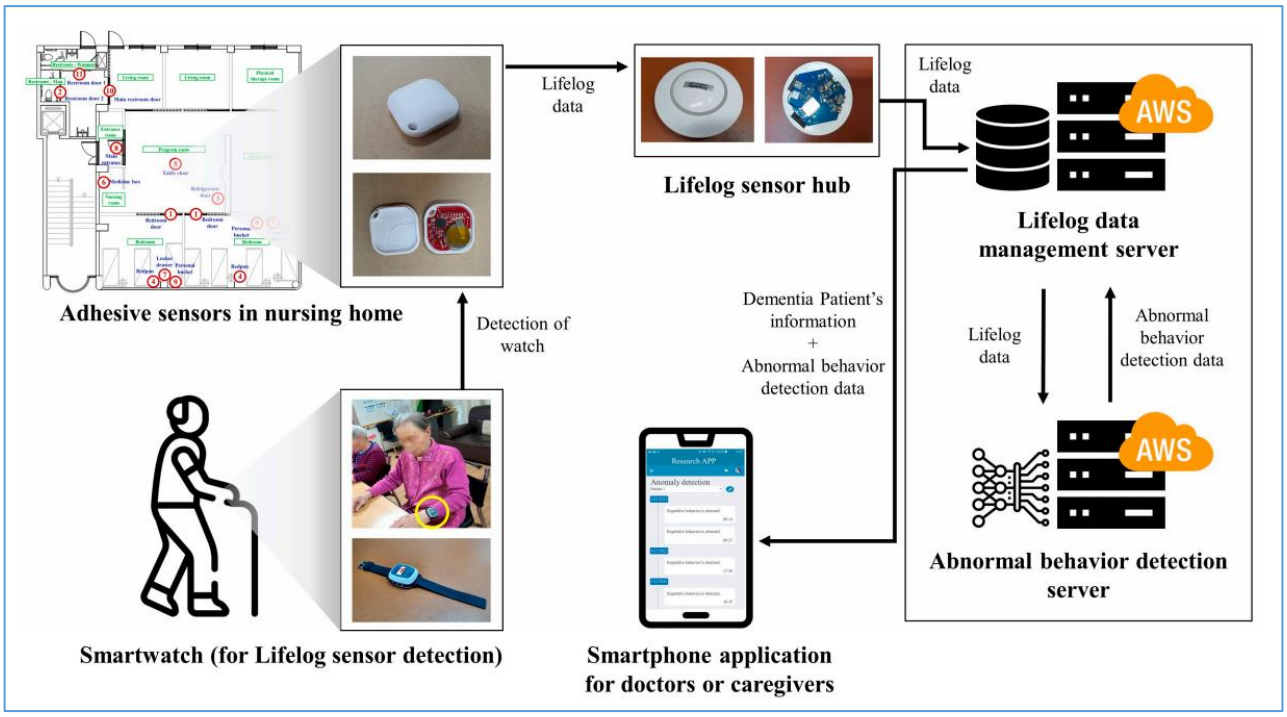


Figure 2. Machine Learning-based system for detection of abnormal behavior in dementia Patients [17]. (Open Access).

6.5 Strengths and Challenges of AI in Daily Living Assistance

AI-based daily living support can provide independence, safety, and reduced caregiver burden, while AI-based monitoring, responses, and adaptability can support care around the clock, and scalable solutions can be more convenient and person-centered to serve the dementia individual effectively. There are also challenges. The barriers to implementation for assistive technology include cost, usability, and acceptance concerns with the person with dementia - resistance to technology use and feeling overwhelmed with technology are often the issue [35]. Privacy issues can arise in that continuous monitoring creates confidential data that must be managed. Finally, over-dependence on AI tools diminishes valuable human association that tools do not provide, which is required to enhance emotional health and wellbeing for a person with dementia.

7. Integrated Perspective of Diagnosis and Daily Living Assistance

The two areas of artificial intelligence in dementia—detecting and diagnosing dementia (Section 5) and assisting people living with dementia in their day-to-day lives (Section 6)—can be best understood within a single continuum of care. Most current work using artificial intelligence in dementia detection and diagnosis involves developing models that use neuro-imaging, cognitive assessments/behavioral evaluations, or biomarkers to identify dementia earlier than would occur without such models. These include, among others, neural networks based on electroencephalographic (EEG) readings, deep-learning models applied to neuro-imaging (MRI/PET scans), and voice-based cognitive assessments [1-2, 8, 27, 34]. However, like many other diagnostic tools developed to date, they are limited in how effective they will be if they do not extend beyond providing diagnostic information to supporting a person's daily life. In contrast, the technologies described in Section 6—assistive robots, smart homes/Ambient Assisted Living (AAL) technology, and conversational agents/wearable sensors—were created to assist individuals with dementia in their day-to-day activities and improve their quality of life [7, 9]. While there has been evidence showing that socially interactive robots and assistive robots can help improve the emotional well-being and socialization of people with dementia [26, 30]; and smart home/IoT-based technologies allow for constant monitoring and support, most of these assistive systems currently function independently of the diagnostic results that could potentially be used to make informed decisions about what type of support would be most beneficial to the individual [6, 20, 41]. Therefore, a disconnection becomes apparent between clinical assessment and practical application in care delivery.

An integrated approach will bridge this gap by allowing diagnostic outputs to inform/and/or direct assistive interventions. In particular, AI-based diagnostics can provide critical input regarding the stage of the disease, the cognitive capabilities of the patient, and the patient's behavioral characteristics, which can then be taken advantage of by daily living assistance systems to provide tailored support. For example, data collected from behavioral monitoring and activity recognition models [17-18] can be used by assistive systems to create more targeted interventions; and continuous monitoring provided through systems embedded in smart homes and wearable devices can provide additional insight into a patient's behavior and continually refine the diagnostic model [28, 41]. Essentially, this creates a feedback loop in which diagnosis informs assistance, and ongoing real-time monitoring continues to refine diagnostic accuracy. Additionally, advances in AI (multimodal learning/federated learning) now permit the integration of various disparate data sets (neuro-imaging data, physiological signals, etc.) and behavioral data collected in real-world settings [28, 31]; and reinforcement learning allows AI to continue learning from interactions with patients and adaptively modify its recommendations for interventions accordingly [32]. Although these advancements are promising, numerous challenges hinder widespread adoption (data fragmentation, lack of interoperability, privacy concerns, limited real-world deployments) [4, 9, 33]. Thus, a combined AI-driven care system that links dementia detection/diagnosis with daily living assistance will ultimately enable comprehensive, patient-centered care. Furthermore, this perspective will make individual AI applications more effective and foster intelligent, adaptive dementia care systems capable of continued adaptation.

8. Ethical, Social, and Implementation Considerations

8.1 Ethical and Privacy Concerns

Introducing AI into dementia care raises important ethical concerns. Ongoing surveillance through smart homes, wearable devices, and AI-enabled cameras will produce continuous streams of sensitive personal data, including health status, location, and behavioral data. Ensuring that data is not compromised and not misused is absolutely paramount. A critical issue regarding informed consent involves individuals with dementia [36]. They may not fully understand what they are providing consent to when it comes to sharing their data or allowing it to be monitored. Care providers and healthcare providers must ensure AI upholds patient dignity and autonomy while improving caregiving practice.

8.2 Equity and Access

AI-powered dementia care technologies can rely on complex physical infrastructure, high-speed internet, and expensive devices, limiting use among patients in low-resource or rural settings. This increases the potential for health disparities to emerge along socio-economic lines. Additionally, most AI models are trained on datasets from high-income countries, limiting their generalizability to other cultural and ethnic groups. Ensuring equitable access to AI for dementia care requires policymakers to provide programs that subsidize use and fund on-site, individualized AI solutions developed specifically for underrepresented groups [37].

8.3 Human–AI Collaboration

AI in dementia care should supplement, not replace, caregivers. While robots and chatbots may help with routine tasks or social visits, humans still provide meaningful human connectedness (or empathic contact), complex decision-making, and attachments that provide empathy. Ultimately, success in dementia care will come from new AI systems that augment and enhance the caregiving role, not replace it [38]. Examples of human-AI collaborative models (for example, caregiver dashboards or decision-aiding systems) show how the technology supports caregivers rather than removing the caregiver role from the encounter.

8.4 Usability and Technology Acceptance

The usability of AI systems is a major factor in the success of dementia care. Technologies must have simple user interfaces, account for potential cognitive decline, and reflect cultural humility. Acceptance also depends on trust: patients and caregivers should believe AI tools are safe, effective, etc. Resistance to technology often stems from concerns about its intrusiveness or complexity. Development teams can increase

acceptance by involving those who will use the system in interactive design so solutions meet real needs and preferences [39].

8.5 Policy and Regulatory Frameworks

Guidelines, standards, and certification approvals will be critical to using AI in dementia care safely and accountably. Regulatory authorities need to develop and implement guidelines to support assessing the efficacy and reliability of AI-based health care products and services. Data governance will also require transparency, fairness, and accountability for all AI-based decision-making [40]. Standardization in both areas will require collaboration of various stakeholders (i.e., ethical review boards, health care organizations, and technology developers) to formulate a set of standards collaboratively. The standards will protect vulnerable patients and foster innovation.

8.6 Data Governance and Risk Mitigation Strategies in AI-Based Dementia Care

While many agree that privacy, fairness, and consent issues associated with AI in dementia care are important to consider, we must develop formal frameworks for managing data and mitigating risk before we can create an environment for successful, safe, large-scale deployment of AI in dementia care. Systems designed to manage dementia will depend on a variety of multimodal data (neuroimages, audio/video, behavior, etc.) gathered through neuroimaging and speech analysis, wearable devices, and smart homes [28], [31, 42]. These data types present challenges related to security, ownership, transparency, and regulatory compliance [4, 9]. Data governance provides the structure needed to ensure adherence to established standards and regulations governing the collection, storage, and processing of health-related data. Data governance provides the structure to protect the confidentiality, integrity, and availability of personally identifiable information (PII) by controlling how data is accessed and used. Examples include implementing encrypted storage methods and secure access protocols to limit unauthorized access to PII [20], and implementing "data minimization" strategies to collect only what is needed and retain it no longer than is reasonable based on the purpose for which it was collected [9]. Additionally, effective data governance models should establish clear definitions regarding data ownership and accountability within a system consisting of multiple stakeholders (healthcare providers, caregivers, software vendors, etc.) [32]. To further protect patients' rights to privacy, various techniques exist for preserving the privacy of individuals participating in studies involving AI models. Examples include Federated Learning and Anonymization. With Federated Learning, an AI model learns from distributed data across numerous locations without ever accessing any individual's raw patient data [28]. Both Federated Learning and Anonymization help ensure that an organization complies with changing laws and regulations governing the handling of protected health information. However, organizations using anonymized data face one challenge. Organizations using anonymized data must determine whether combining two or more datasets could identify an individual [9].

In addition to establishing governance structures, organizations must develop risk mitigation strategies at every stage of the AI model development life cycle. Two primary areas of concern during AI model development include bias from training on non-diverse datasets and model reliability/robustness during operation in a real-world setting. As previously mentioned, bias can lead to inaccurate or unfair results for specific patient populations if the dataset(s) utilized to train the model do not reflect those populations [31, 42]. To reduce the likelihood of biased results, organizations must use diverse, representative training datasets and periodically review their models for bias in both performance metrics and decision-making processes. For model reliability/robustness, organizations must continue to evaluate models for accuracy and stability as they evolve and operate under varying levels of uncertainty due to differences in data quality across operational settings [19].

Deploying supportive technologies also presents operational risks. Risks include false positives/alarm fatigue, technology failures, and unvalidated/unintended AI-based decisions that impact patient safety. To mitigate some of these risks, organizations should implement human-in-the-loop (HITL) mechanisms into their systems. HITL mechanisms allow clinicians/caregivers to monitor and approve/reject AI-driven recommendations/orders before implementation [5, 7]. Additionally, these systems should include fail-safe and/or alert-verification mechanisms to prevent critical errors in real-world settings [6, 41].

Transparency and accountability are equally important components of both good governance structures and appropriate risk mitigation strategies. For example, organizations should document all uses of patient data collected through their systems to create audit logs that regulators can review [14]. In addition, organizations should clearly document system architecture/designs/ intended use cases so clinicians and caregiver users can understand each system's functionality and use-case limitations. Documentation will facilitate adoption/responsible use of these systems while fostering trust between clinicians/caregivers/users and AI-based systems [32].

In conclusion, developing strong data governance structures and risk-mitigation strategies is crucial to ensure the trustworthy deployment of AI in dementia care. Only by using secure data management practices, privacy-preserving techniques, addressing bias [42], and providing clinician/user oversight will AI systems not only perform well technically but also meet regulatory requirements and earn the trust of clinicians/users/caregivers.

9. Research Gaps and Future Directions

9.1 Need for Longitudinal Studies

Most current AI models for dementia detection and care were trained and validated on short-term and cross-sectional datasets. These models provide the accuracy we would expect in commercially controlled settings but do not reflect the progressive and heterogeneous nature of dementia. Longitudinal studies are necessary to understand how AI tools are monitored and evaluated over the long term and across the later stages of dementia [43]. These types of studies would allow models to recognize and track disease progression over time, adjust interventions over time, and predict future care requirements.

9.2 Integration of Multimodal Data

Dementia is a multifactorial condition impacted by the interdependence of brain imaging, genetic risks, speech patterns, lifestyle choices, and behavioral changes. Currently, almost all AI studies focus on single data streams (such as MRI scans or speech). Research should pursue multimodal AI systems incorporating imaging, biomarkers, wearable data, and cognitive assessments. Multimodal integration of information from diverse sources presents the opportunity for AI to achieve greater accuracy for diagnostic interventions and customized care strategies.[44]

9.3 Personalized and Adaptive AI Care Systems

Dementia patients experience a significant array of symptoms, trajectories, and care needs. AI-based tools often provide generic, one-size-fits-all recommendations that do not account for the individual patient. Future research may explore implementing personalized AI systems that offer individual patients recommendations based on their medical history, disease stage, and consistent caregiver feedback [45]. Adaptive AI methods to the patient's behaviors and feedback would enhance the validity and efficacy of care.

9.4 Explainable and Transparent AI (XAI)

Many AI systems developed for dementia research, particularly deep learning architectures, behave as "black boxes" and do not disclose how they arrived at a decision. This opacity decreases trust in the system by clinicians, caregivers, and patients alike. Developing XAI (explainable AI) frameworks is imperative to detail the decision processes used for frames, highlight key features that drive predictions, and gain validation from clinical stakeholders [46]. Model interpretability, when evaluated, is an important factor in predicting regulatory acceptance of the approach. A fundamental component of successful AI use in dementia care is the development of explainable artificial intelligence (XAI). Transparency in decision-making in clinical environments will be critical to the implementation and success of AI systems in dementia care. Most advanced AI models, particularly deep neural networks (DNNs), transformers, and multimodal learning architectures, have shown superior accuracy in dementia diagnosis and prediction tasks [14],[34] but remain "black box" models. As a result, they limit clinicians' willingness to adopt AI systems because clinicians cannot explain, validate, or understand the rationale behind AI-generated diagnostics/treatment plans.

Clinical decision-making fundamentally depends on interpreting information. Clinicians must develop and defend diagnostic and treatment recommendations using understandable evidence; however,

they cannot produce evidence from AI systems whose results are generated by algorithms that are unknown or uninterpretable. Consequently, this lack of explainability creates barriers to adopting AI systems in clinical practice. [47] For example, while DNN-based models for diagnosing dementia may generate high-accuracy classifications, they may not indicate which aspects of the neuroimaging were used to make the classification. Therefore, if clinicians cannot interpret the logic behind AI-generated diagnostics/treatment plans, they will be unable to develop sufficient trust in them and subsequently incorporate them into existing clinical practices. Similarly, clinicians using cognitive/behavioral assessments and corresponding AI systems need to discern how specific factors, such as speech patterns or activity changes, correlate with declining cognition. Without such explanations, clinicians may view AI systems as unreliable/non-actionable. Feature attribution methods (SHAP/LIME), attention mechanisms, and saliency mapping represent examples of XAI techniques designed to provide interpretable insights regarding how a given model made its decisions. In dementia care, XAI methods can provide evidence of relevant biomarkers, brain areas, or behavioral characteristics that contribute to predictive outputs aligned with clinical reasoning. For example, XAI-based neuroimaging models can display visual representations indicating brain regions associated with Alzheimer's disease progression. These visual representations would allow clinicians to cross-validate AI-generated outputs with their own domain expertise. Similarly, XAI-based models analyzing speech/activity data can point out specific cognitive indicators related to Alzheimer's disease. Such findings could increase clinician confidence in diagnosing Alzheimer's disease.

While diagnosis represents one area where XAI provides value, it is equally important in assisting systems used for daily living activities. AI-driven technologies that support patients with daily living activities, such as smart homes, wearable monitors, and socially assistive robots (SARs), often autonomously generate decisions that affect patient safety and well-being. The lack of transparency in these systems can negatively affect user acceptance, especially among caregivers who need to understand why particular actions (e.g., alerts/reminders/environmental modifications) occur. Integrating XAI into these systems could improve usability by generating clear, human-interpretable explanations. Improved usability would increase caregiver trust and strengthen collaboration between humans and AI systems. As mentioned previously, integrating XAI presents numerous challenges. A major challenge is that most AI models exhibit an inverse relationship between accuracy/model performance and interpretability. More complex deep learning models (highly accurate) are generally less interpretable than simpler machine learning models. Another limitation of many XAI methods is that they generate post hoc explanations that may not accurately reflect the model's inner workings, limiting explanation credibility. Finally, as stated earlier, no standard evaluation metrics /frameworks currently exist to assess the quality/explainability of XAI-based solutions in healthcare applications. [48]

Despite these limitations, XAI will help bridge the gap between innovative AI solutions and real-world clinical adoption. Future research should focus on developing intrinsically interpretable AI models, creating XAI-based solutions for specific domains (dementia care), and establishing standards for evaluating the quality of explainability in health-related applications. Integrate XAI into multimodal, adaptable AI solutions capable of generating transparent/personalized/clinically actionable decision support.[49] Overall, the use of transparent/interpretable AI will play a key role in ensuring that AI-enabled dementia-care solutions not only demonstrate acceptable levels of accuracy but also acceptability/trustworthiness/ethics in clinical-practice settings

9.5 Policy, Standards, and Interdisciplinary Collaboration

AI in dementia care is situated at the crossroads of medicine, computer science, psychology, ethics, and policy. But research remains ensconced in disciplines. Future advances will depend on interdisciplinary work to address both technical and human-centered challenges. International policymakers will also need to develop standards for AI-supported dementia tools, including how well they meet requirements for safety, fairness, and access. Collaborative engagement across academic, industry, and health institutions will accelerate innovation while ensuring responsible use [50].

10. Conclusion

Artificial intelligence is rapidly transforming dementia care by providing powerful tools for early diagnosis and daily support. For diagnosis, AI will improve the sensitivity of neuroimaging, speech assessment, and biomarker assessment, enabling earlier detection of cognitive decline than prior methods. Additionally, AI in assistive technology—smart homes, wearables, conversational agents, and social robots—will enable greater independence, safety, and quality of life for patients, while reducing strain on caregiving systems and healthcare.

Even with these improvements, challenges remain. Ethical challenges, such as privacy and data security issues, unequal access to technology, and over-reliance on machines, show that we should still be moving cautiously and in a fair manner. Existing research also suffers from short-term data use, limited customizability, and a lack of transparency in AI decision-making. We should not pursue innovation until we develop longitudinal, multimodal, or explainable AI models, alongside strong policies and cross-disciplinary collaboration.

In short, AI can bridge large chasms in dementia care—from improved diagnosis to daily assistance—but we will only succeed if we align values with technological advances. By bringing together medicine, computer science, ethics, and public policy, we can advance AI solutions that improve clinical utility while enhancing the dignity, autonomy, and quality of life of people living with dementia.

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