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Integrating Machine Learning and Advanced Technologies for Enhanced Prediction and Treatment Strategies in Dementia and Related Diseases

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ABSTRACT

Dementia and its accompanying neurodegenerative diseases represent some of the most challenging clinical problems and require new solutions for early detection and individualized therapy. In this research, various Machine Learning (ML) approaches and advanced technology integration are evaluated, which is a crucial aspect for improving disease diagnosis, monitoring, and treatment strategies, especially in the context of dementia management. According to the research, all supervised, unsupervised, and deep learning algorithms lead to the integration of large demographic data sets such as neuroimaging biomarkers and electronic health records, which will ultimately contribute to not only diagnosing diseases more accurately but also predicting their progression. This research utilizes a mixed-method approach to gather survey data from 300 participants, including patients, caregivers, and healthcare providers. The study also found that there was strong interest in gap-filling AI-powered tools despite the barriers of digital literacy, cost, and data privacy concerns. In this work, these researchers aim to propose a framework by which existing ML models are integrated with the flow of patient-related data, to facilitate clinical decision-making and personalized interventions. It ultimately describes interdisciplinary collaboration, ethical safeguards, and accessible technological infrastructure as a means of achieving what AI can do in dementia care. This study signals a shift towards proactive, person-centered, technology-facilitated healthcare for older people.

Keywords: *Artificial Intelligence, Disease, Dementia, Machine Learning, Medical, Patient.*

1. INTRODUCTION

One of the most complex organs in the human body is the brain. There are more cells in this confusing maze of billions of neurons than there are stars in our galaxy, along with many supporting actors, most notably microglia. The intricacy of the brain has made it particularly hard to understand how neurological disorders develop or how a healthy brain functions (Aging, 2023). The symptoms of AD, an age-related progressive neurodegenerative disease, consists of cognitive impairment, behavioral and memory abnormalities, and more. Between 60 and 80 percent of dementia cases are caused by Alzheimer's disease, the most prevalent underlying disease. However, the building up of tau formations and amyloid-β plaques, which eventually result in neuronal and synaptic damage, provides proof of the pathological features that are notoriously linked to AD because of the extensive neuroscience research conducted on human as well as animal subjects (Kale et al., 2024). In addition to making everyday living more difficult, these neurological changes impair cognitive abilities including memory, language, and executive function. It is an almost gradual process that happens in stages, ranging from early mild cognitive impairment (MCI), when symptoms are mild and do not interfere with day-to-day activities, to more serious stages of dementia, where individuals lose their ability to speak, grows into unable to recognize loved ones, and start to establish a self-care routine (Gauthier et al., 2022). The effect of AD has a significant influence on caregivers, medical facilities, and society as a whole, and its incidence continues to increase worldwide as people age. Even now, the disease is still regarded as incurable. However, advancements in computers and technology are altering that. Indeed, AI and ML are powerful tools for dementia research because they enable researchers to weave together diverse pieces of information to create a more coherent narrative about the disease. AI is the process by which machines mimic human intellect. It makes use of "algorithms," or computational recipes, which enable computers to carry out activities that often call for human intellect. A kind of AI called ML enables an algorithm to become smarter with time and feedback.

Dementia is a mental disorder marked by a progressive loss of cognitive function that may affect daily activities such as memory, problem-solving, visual perception, and focus. Elderly people are often the most vulnerable to dementia, and it's a common misconception that this is an inevitable aspect of aging. Although dementia is not a normal part of aging, it needs to be seen as a severe case of cognitive decline that affects daily functioning (Figure 1). The main causes of dementia include a number of diseases and traumas that affect the brains of people (Lo, 2017). Dementia is the seven leading cause of death globally. It is also the leading cause of dependence and disability in older adults globally (World Health Organization, 2025). The diagnosis of dementia requires both a change in the patient's usual functioning and unambiguous signs of a serious decline in thinking (Kirshner, 2012).

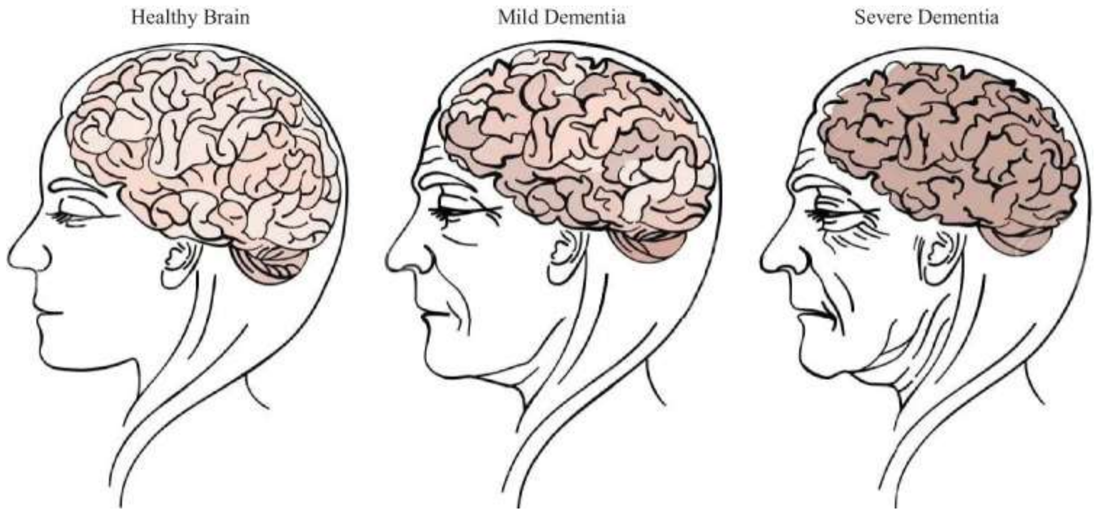

Figure 1: Age-Related Dementia Progression (Javeed et al., 2023).

2. LITERATURE REVIEW

Javeed *et al.* have proposed to do an exhaustive assessment of (ML)-based autonomous diagnostic systems by including a variety of data modalities, including image, clinical feature, and voice data. It used the search phrases dementia, machine learning, feature selection, data methods, and automated diagnostic systems to gather research papers from 2011 to 2022. The decisions were examined and discussed. Image data-driven machine learning models provide favorable results for dementia prediction when compared with different data modalities, such as clinical feature-based data and voice data. In addition, this SLR identified the flaws in the previously proposed automated dementia procedures and offered solutions for development (Javeed et al., 2023).

Khare and Acharya (Khare & Acharya, 2023) In that work, a new adaptive-interpretive network architecture called Adazd-Net is presented, which allows for automated AZD recognition from EEG data. It proposes an automated method of adapting to rhythmic variations in the EEG the adaptive flexible analytic wave transform. The ideal channel with good discrimination and a suitable number of characteristics for the system's effective functioning is also investigated. Its presented in the research is the approach used to describe each system and the classifier model's overall prediction. With a 10-fold cross-validation method, they were able to detect AZD EEG signals with 99.85% classification accuracy. It developed a method for identifying AZD that is accurate and comprehensible. Our suggested technique may reveal many of these hidden aspects of modification during AZD to doctors and scientists. Due to its accuracy and efficiency, our Adazd-Net model may be used to identify AZD in actual medical settings.

Nykoniuk *et al.* (Nykoniuk et al., 2023) examined the ML techniques that have established an efficiency for AD classification from medical images including "Magnetic Resonance Imaging" (MRI). Individual ML models either overfit and perform poorly or are unable to model all the complexities present in the data. In that study, a set of ML models is proposed to characterize and improve the classification of individuals who will develop AD. The ensemble will predict the output based on Random Forest, Multi-Layer Perceptron, and SVM predictions. The final ensemble model achieved an accuracy of 96% in classifying patients into five different AD stages: cognitively normal, early-onset MCI, late-onset MCI, MCI, and AD dementia.

Srithaja *et al.* (Srithaja et al., 2023) explored Alzheimer's and observed that his brain and surrounding nerve cells were very weak. In terms of medicine, it is triggered by the abnormal accumulation of proteins in and around brain cells. There are two proteins involved: tau and amyloid. Among the numerous recognized risk factors for AD, one of the various forms of dementia, contain age, history of family members, accidents to the head, etc. Those over 60 were often impacted, but middle-aged people are now also afflicted. This has led experts to focus on this disease and employ diverse investigation techniques in an attempt to control it. At first, they focused their attention on hearing to find a cure for this disease, but after some time they started focusing on disease analysis and prediction. Early-stage identification is important to treat AD efficiently and recover from it. ML algorithms are used to build the required model to give accurate results. It provides users with stage-wise prediction of AD in this study. It has 4 stages - non-deranged, mildly deranged, moderately deranged and deranged. It is a very dreadful disease and sadly there is no cure so we can only slow down the progress of the disease.

(Ford et al., 2019) has discussed patient records from the Clinical Practice Research Datalink (CPRD). It used a case-control design, identifying patients over the age of 65 with a diagnosis of dementia (case patients) and matching them 1:1 by gender and age with patients without evidence of dementia (control patients). It generated a screening list of 70 clinical entities associated with documented dementia events in the 5 years before diagnosis. After converting to binary data, it was able to distinguish cases from controls using machine learning classifiers such as logistic regression, Naïve Bayes, support vector machines, random forests and neural networks. Its analysis identified the most determinant features driving discrimination. The logistic regression, SVC and neural network stroke risk prediction models may be beneficial to GPs or healthcare planners in patients with early-stage dementia. Future studies could refine this model by analyzing the longitudinal nature of patient data and modelling the gradual decline in function over time.

Objective

The present study aims to summarize ML applications for dementia and other neurodegenerative diseases concerning prediction, diagnosis, and treatment. It is used in neuroimaging, biomarkers, and electronic health record data for diagnosis and prediction of the disease. Moreover, this study will evaluate aspects of adherence or no adherence, user perception, the potential effect of care of wearable devices and digital health tools on patients, caregivers, and health professionals, and finally will propose a person-centered, technology-enabled model of individual dementia care and clinical decision support.

3. METHODOLOGY

3.1 Research Design

In this mixed-methods research design, both quantitative and qualitative methods are used to develop, evaluate, and implement ML-based predictive models that facilitate dementia diagnosis and treatment selection. Combining statistical analyses with experiential insights, the study provides a robust representation of clinical patterns, patient needs, and, clinical technology performance to provide insights helping the development of accurate and reliable predictive tools. The study emphasizes the need for an all-encompassing AI-based framework driven by neuroimaging and IoMT technologies. These tools are used to enable early identification, ongoing assessment, and improved treatment approaches for dementia and related neurodegenerative disorders. The purpose of combining these technologies is to revolutionize conventional diagnostic channels leading to more individualized, fast, and effective healthcare interventions.

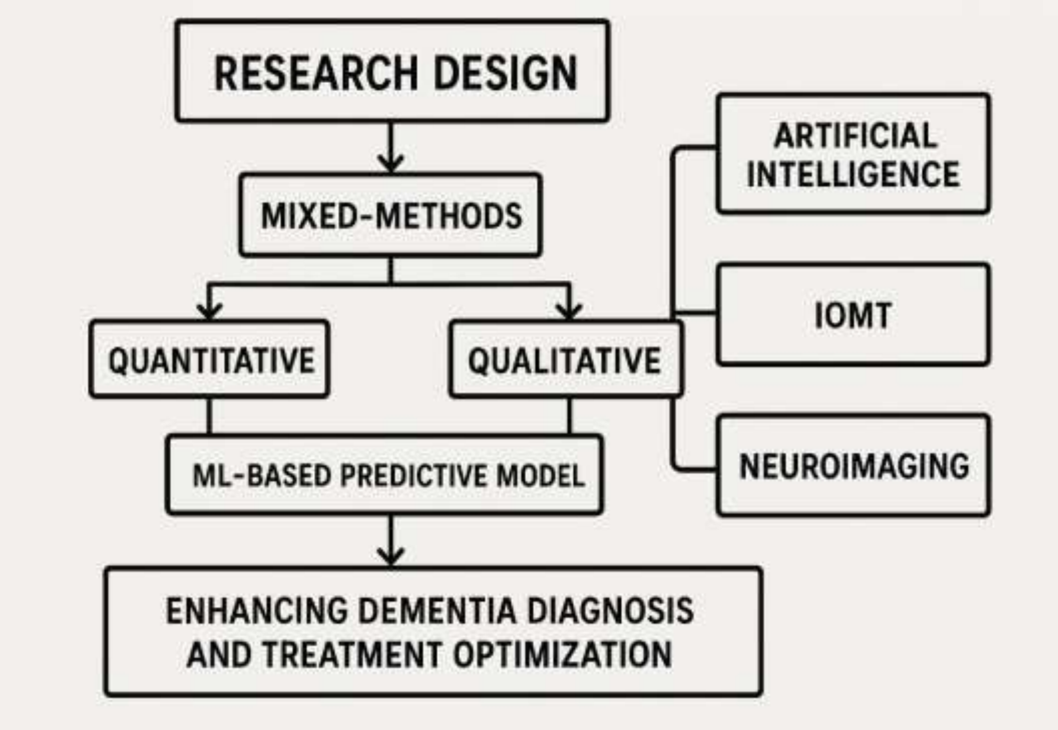

Figure 1: Research Design Framework for Enhancing Dementia Diagnosis and Treatment Optimization.

3.2 Sample and Instrument

Purposive sampling will be utilized to select 300 participants in total, ensuring representation from pertinent parties involved in dementia care and the implementation of technology. The Patients diagnosed with dementia or related neurodegenerative diseases (n =100), caregivers and family members of patients (n =100), and healthcare professionals (neurologists, psychologists, therapists, nurses) (n = 100). Dementia and related neurodegenerative disorders represent a growing global health challenge, particularly with aging populations worldwide. It is essential to understand the demographics of those impacted by or providing dementia care to provide individualized, successful treatments. In this study, a sample of 300 participants including patients, caregivers, and healthcare professionals was surveyed to gather essential demographic data in Table 1. This information provides valuable insights into age distribution, gender, education levels, occupation, and living environments, all of which can influence disease progression, care strategies, and the adoption of emerging technologies such as machine learning and smart healthcare systems.

Table 1: Represent the demographic profile of 300 participants.

Variable	Category	Frequency (n)	Percentage (%)
Age Group	18–30 years	40	13.3%
	31–45 years	85	28.3%
	46–60 years	110	36.7%
	61+ years	65	21.7%
Gender	Male	160	53.3%
	Female	135	45.0%
	Other	5	1.7%
Education Level	No formal education	15	5.0%
	Primary and Secondary	60	20.0%
	Graduate	135	45.0%

	Postgraduate and above	90	30.0%
Occupation	Healthcare professionals	100	33.3%
	Family members	100	33.3%
	Dementia patients	100	33.3%
Location	Urban	190	63.3%
	Semi-urban	70	23.3%
	Rural	40	13.3%
Marital Status	Single	90	30.0%
	Married	180	60.0%
	Divorced	30	10.0%

3.3 Inclusion Criteria

Assurance participants reported any direct involvement with dementia care, either as a healthcare professional or family caregiver and were aged 18 years old and above with a clinical diagnosis of dementia. Study participants had to be in a position to give informed consent and could understand the questionnaire/interview format, independently or with minimal assistance. Participants (healthcare professionals or caregivers) were required to provide care experience of one (healthcare professional) or six months (caregiver) respectively with the patients with neurodegenerative disorders. Other participants involved in technology integration aspects also had consideration for access to basic digital tools, for example, smartphones or the internet.

3.4 Exclusion Criteria

The starkest exclusion criteria were any associated significant cognitive or communication impairment that made it impossible to enroll someone in the study meaningfully, and/or a lack of a caregiver or an assistant to help with data collection. Participants were excluded who had histories of no comorbid psychiatric or neurologic disorders serious enough to interfere with the findings. In addition, those participating in any other intervention trial, or one that uses an artificial intelligence or digital healthcare tool were excluded to prevent overlap or bias in data interpretation. Participants who responded incorrectly in the survey phase or whose responses were inconsistent were excluded from analyses.

3.5 Data Collection

This research gathered data through a mixed-mode approach using both online questionnaires and face-to-face interviews, to suit the varying needs of the population under study. Online surveys were conducted via Google Forms and Qualtrics, targeting mainly healthcare professionals and caregivers who had a greater chance of possessing adequate internet access and digital literacy skills. Cognizant of our target population, particularly those without technological access or experiencing cognitive difficulties, face-to-face interviews were undertaken if needed (often with family members or trained facilitators helping the interview process). This combination enables more flexibility and inclusivity among participant groups.

Findings from the health and tech use survey provide a holistic view of the way 300 participants manage their health and use tech for dementia care. The data show that, while most have not yet used AI-powered tools or wearables, there is increasing receptiveness to using technology, as a large proportion of respondents indicate a willing or conditional willingness. Despite the growing usage of mobile health apps, levels of comfort concerning their interface differ, emphasizing the need for both user-friendly designs as well as digital literacy support. It also shows key barriers like training, cost, and connectivity that could prevent wider adoption. We believe these findings provide a unique and relevant snapshot of current integrations, trends, attitudes, as well as points of intervention for the integration of advanced technologies in healthcare.

Table 2: Represent the survey responses on health and technology use.

Survey Question	Response Option	Frequency (n)	Percentage (%)
What type of dementia or cognitive condition has been diagnosed (if applicable)?	AD	55	18.3%
	Parkinson's Disease	20	6.7%
	MCI	15	5.0%
	Other	10	3.3%

	Not Applicable	200	66.7%
How many years have passed since the diagnosis?	Less than 1 year	25	8.3%
	1–3 years	35	11.7%
	3–5 years	25	8.3%
	More than 5 years	15	5.0%
	Not Applicable	200	66.7%
What type of treatment is currently being followed?	Medication only	40	13.3%
	Therapy only	20	6.7%
	Both medication and therapy	35	11.7%
	No treatment	5	1.7%
	Not Applicable	200	66.7%
Do you or the person you care for use wearable health-monitoring devices (e.g., smartwatches, fitness bands)?	Yes	110	36.7%
	No	190	63.3%
How comfortable are you with using mobile health apps (e.g., for tracking health, reminders, or exercises)?	Very Comfortable	85	28.3%
	Somewhat Comfortable	105	35.0%
	Not Comfortable	110	36.7%
How often do you or the person you care for access the internet?	Regularly	150	50.0%
	Occasionally	80	26.7%
	Rarely	45	15.0%
	No access	25	8.3%
Have you ever used any AI-based tools or applications for dementia care or diagnosis?	Yes	65	21.7%
	No	185	61.7%
	Not Sure	50	16.6%
Would you be willing to use advanced technologies (e.g., AI, smart devices) to assist in dementia care?	Yes, definitely	120	40.0%
	Maybe	130	43.3%
	No	50	16.7%
How effective do you think technology is in enhancing the quality of life for dementia patients?	Very effective	90	30.0%
	Somewhat effective	135	45.0%
	Not effective	45	15.0%
	Don’t know	30	10.0%
What challenges do you face (or expect to face) when using technology in dementia care? (Select all that apply)	Lack of knowledge	140	46.7%
	Cost of devices	125	41.7%
	Resistance from patient	100	33.3%
	Data security concerns	95	31.7%
	Technical	110	36.7%

	None	40	13.3%

3.6 *Data Analysis*

Analysis of primary data source and distribution of primary source data collection methods used in the study with 300 respondents Surveys were the most commonly used approach (n = 180), which likely reflects both their efficient data collection and ease of distribution, particularly among caregivers and healthcare providers. Narrative Interviews were done with 50 and used observation data mostly from inpatient settings for 30. Focus groups and device-based measurements each contributed data from 20 participants, offering qualitative depth and objective health indicators, respectively in Figure 2. This wide range of techniques provided thorough and trustworthy primary data that was appropriate for the goals of the research.

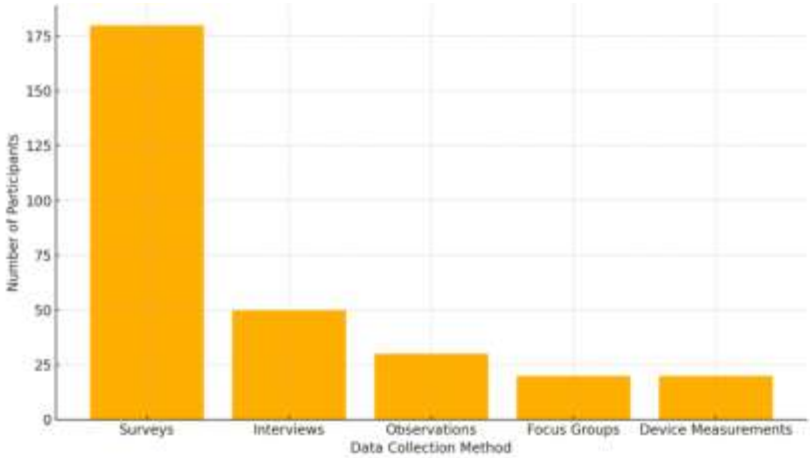

Figure 2: Distribution of Primary Source Data.

It draws upon second-order data, important features of technology use, and willingness in the 300 people sampled in the study. The study also showed that a comparatively high proportion of respondents (43.3%) said they would actively consider advanced technologies in dementia care only in the right circumstances, and a further 40% were generally supportive of such innovations. However, the real use of AI-based tools stands at 21.7%, which means that people are willing to use AI-based tools but the actual use is much less. To complicate matters, adoption of wearable devices remains low with just 36.7% reporting use. The level of digital readiness is mixed among participants, as comfort with mobile health apps is evenly split. In summary, the chart underlines a genuine potential for tech integration, with the right tech applied, only if barriers like awareness accessibility, and training are overcome. Figure 3 provides a visual swift of major categories related to technology use and perception.

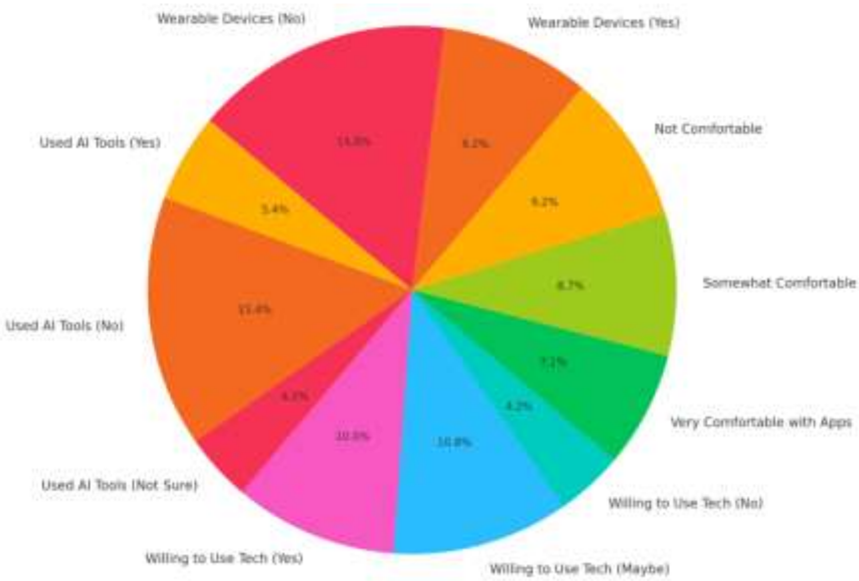

Figure 3: Distribution of Participants' Responses on Technology Use and Comfort Levels in Dementia Care.

4. RESULTS

The finding of this study provides important information about the adoption and acceptability of technology in dementia care. As shown in Figure 4, most participants were willing to use advanced technologies, as 40% (120 participants) reported that they would be willing to use such tools and 43.3% (130 participants) said they would be willing under certain conditions. Only 16.7% (50 participants) were not interested in using technology. This indicates a great potential for the use of digital solutions in dementia care, as long as users' doubts are properly addressed.

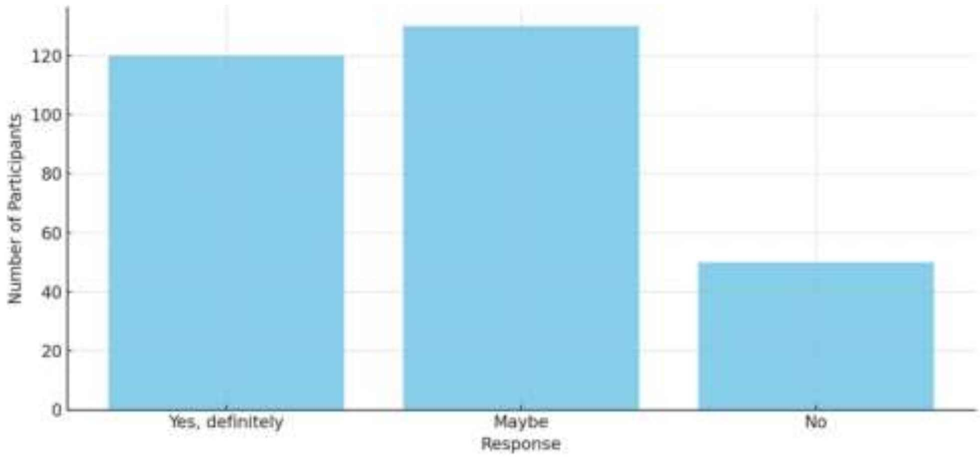

Figure 4: Represent the participant's willingness to use technology in dementia care.

These barriers to technology adoption in this analysis are important to understand why there is a gap between interest and implementation which can be seen in Figure 5. The most frequently mentioned barriers were lack of training and digital literacy (46.7%), followed by cost-related barriers (41.7%) and patient resistance (33.3%). Other significant barriers included privacy concerns (31.7%) and technical connectivity issues (36.7%). Of note, only a small proportion (13.3%) reported no barriers, meaning that most participants experience at least one barrier to effective technology integration.

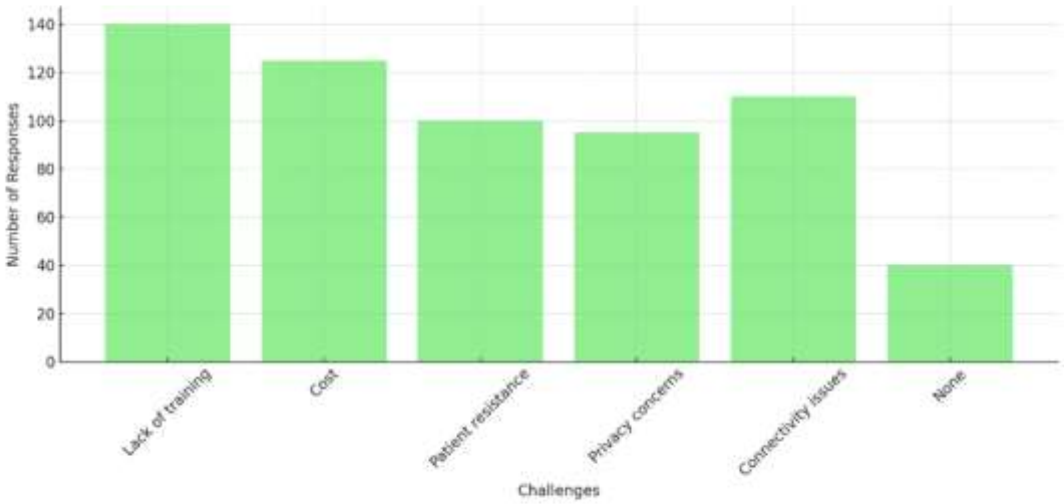

Figure 5: Challenges faced by using technology for dementia care.

All these findings underscore that despite in general positive views about the role of technology in dementia care, barriers related to practicalities and infrastructure have to be overcome. Focused training, low-cost devices, simplified user interfaces, and dependable connectivity can go a long way in letting technology find its way into this sensitive area of healthcare.

5. DISCUSSION

Technology has attracted growing interest in dementia care over the past five years, with several studies recognizing both the potential improvements and real-world challenges. Our study is under the previously existing data that have shown that dementia caregivers are broadly open toward using advanced technologies. Yet, practical barriers around lack of training, cost, and connectivity prevent mass adoption. The same is found in a systematic evaluation of telemedicine in older adults with AD and related dementias. Although telemedicine has received positive reviews in the literature, successful implementation often depends on 'facilitators', staff, and other care partners who help resolve technical issues. It should be noted that excluding individuals with sensory disabilities from participating in such studies may increase accessibility issues for this population (Yi et al., 2021). The research identifies six key barriers to the adoption and use of technology in dementia care: awareness; product specifications; financial investment; unclear benefits; ethics; and technical limitations. These barriers are interconnected, meaning an integrated, multidisciplinary approach is needed to overcome them (Freiesleben et al., 2021). Furthermore, research on the use of digital health apps by people with dementia has focused on factors that influence use, such as perceived usability of the technology, need for assistance, privacy and trust issues, and physical and design factors such as reduced dexterity. These are just a few of the many factors that indicate how important it is to create a powerful support network to catalyze consumer adoption of user-friendly design and expertise (Sorrentino et al., 2024). Despite initial enthusiasm for the role of technology in dementia care, it is clear from these findings that there are barriers to implementation in practice that can and should be addressed. Such disconnect between interest and implementation can only be reduced through focused training programs and improvements in funding and infrastructure that aim to make a real difference in dementia care.

6. CONCLUSION

In the AI research field for dementia, AI can help make timely and accurate diagnoses, provide an easy cognitive training tool, and reduce the pressure of care. AI can also continuously track the journey from MCI to dementia so that timely interventions can be given to high-risk individuals. The rise of deep learning, especially in image data, can be attributed to its ability to eat up complex data. However, the black box of complex algorithms and explanations makes it inaccessible to clinical researchers. On the other hand, ML and other sophisticated techniques across technology generations come into play, bringing a new architecture for diagnosis, treatment, and prediction in dementia and related disease. Earlier diagnosis of disease, ML methods that parse large datasets including neuroimaging, genetic profile, and behavioral information enable these advancements. This data will allow clinicians to more accurately treat and predict the course of disease in each patient, impacting quality and long-term disease outcomes. Similarly, advanced technologies including wearable devices, brain-computer interfaces, and telemedicine platforms have greatly improved the way patients are monitored and treated, especially in remote or underprivileged communities. AI tools are also being applied in drug discovery and Personalised medicine, and this may enable even more effective treatments. As these innovations advance, it expects to reshape the clinical landscape promising more effective disease management, reduced disease progression, and better support systems for our patients. Therefore, combining ML and advanced technologies is imperative for a more cost-effective and humane dementia care model.

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