Use of artificial intelligence in predicting cognitive decline and dementia: a systematic review

Uso de inteligência artificial na predição de declínio cognitivo e demência: uma revisão sistemática

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Abstract

The use of Artificial Intelligence (AI) and Machine Learning (ML) has been applied in several studies to detect the conversion from mild cognitive impairment (MCI) to dementia. This study aims to identify challenges and effective methods for applying AI in predicting cognitive decline and dementia. A literature review was conducted by searching the PubMed database between May and July 2024,

using predefined eligibility criteria. The analysis included 17 studies involving 12,183 participants (aged 50 to 85 years). The review included 17 articles published between 2015 and 2023, predominantly observational studies. The AI tools applied encompassed demographic and lifestyle data, imaging exams, cognitive tests, biomarkers, and physiological data. MCI was the most prevalent diagnosis among the studies, with a particular focus on the amnestic subtype. Nine studies investigated the conversion from MCI to some form of dementia; four analyzed the prediction of beta-amyloid positivity; three employed ML for diagnostic support in distinguishing controls from patients with different types of dementia; and one assessed the cognitive risk in an elderly population. Among the best-performing approaches identified, multimodal data strategies — especially those involving MRI imaging and sociodemographic information — stood out. Applications involving multimodal datasets, particularly those including MRI exams, improve the overall performance of ML models and are considered among the most effective approaches. Future research should focus on the diagnosis and prediction of less-studied dementias, such as frontotemporal dementia, through the use of AI. The integration of multimodal data, including demographic information, imaging exams, cognitive assessments, and biomarkers, should be encouraged.
Keywords: machine learning; dementia; prediction; mild cognitive impairment

Resumo

O uso de Inteligência Artificial (IA) e Aprendizado de Máquina (AM) tem sido aplicado em diversos estudos para detectar a conversão de comprometimento cognitivo leve (CCL) para demência. Este estudo visa identificar desafios e métodos eficazes para a aplicação de IA na predição do declínio cognitivo e da demência. Foi realizada uma revisão da literatura por meio da busca na base de dados do PubMed entre maio e julho de 2024, utilizando critérios de elegibilidade predefinidos. A análise incluiu 17 estudos, totalizando 12.183 participantes (com idade entre 50 a 85 anos). A revisão incluiu dezessete artigos publicados entre 2015 e 2023, predominantemente observacionais. As ferramentas de IA aplicadas variaram entre dados demográficos e de estilo de vida, exames de imagem, testes cognitivos, biomarcadores e dados fisiológicos. O CCL foi o diagnóstico mais prevalente entre os estudos, com foco no subtipo amnésico. Nove estudos investigaram a conversão de CCL para algum tipo de demência, 4 analisaram a previsão de positividade para o beta amiloide, 3 utilizaram o ML para auxílio diagnóstico entre controles e pacientes com diferentes tipos de demência e 1 avaliou o risco cognitivo de uma população de pessoas idosas. Dentre os melhores desempenhos encontrados nos estudos, destacam-se as abordagens com dados multimodais, por análise de imagens de RM e informações sociodemográficas. Aplicações que envolvam conjuntos de dados multimodais, principalmente com a inclusão de exames de RM, melhoram o desempenho geral dos modelos de ML, sendo essa abordagem tida como uma das mais eficazes. Pesquisas futuras devem focar no diagnóstico e na previsão, por meio da IA, de demências menos exploradas, como a demência frontotemporal. A integração de dados multimodais — abrangendo informações demográficas, exames de imagem, avaliações cognitivas e biomarcadores — deve ser incentivada.

Palavras-chave: aprendizado de máquina; demência; predição; comprometimento cognitivo leve

INTRODUCTION

With scientific advancements, reductions in mortality, and the identification of factors that promote quality of life and longevity, the elderly population has grown significantly worldwide. In Brazil, life expectancy has increased notably. By 2025, the country will be sixth in the global ranking for the number of older adults, with about 32 million individuals aged 60 or older (Milchareck *et al*., 2020; Moreira, 2023; Pereira; Sampaio, 2019). However, this increase in longevity is related to a higher prevalence of chronic degenerative diseases, such as dementia. In 2019, the number of older adults with dementia worldwide was 55 million, with projections to triple by 2050 (Nichols *et al*., 2022). Of this total, 60% live in low and middle-income countries, such as Brazil, highlighting the need for more research on the development of dementia in the elderly population, especially in cases of pre-existing cognitive deficits (Bertola *et al*., 2023; Garcia; Ramos, 2022; Smid *et al*., 2022; Suemoto *et al*., 2023).

Dementia is characterized by cognitive and/or behavioral decline that interferes with activities of daily living (ADLs), resulting in functional impairment compared to previous levels (Smid *et al*., 2022). Cognitive impairment can present itself in different stages, such as subjective cognitive decline (SCD), mild cognitive impairment (MCI), and dementia. These syndromes could be secondary to distinct underlying pathologies such as Alzheimer's disease (AD), frontotemporal dementia (FTD), dementia with Lewy bodies (DLB), and vascular cognitive impairment (VCI) (Nunes *et al*., 2023; Seixas *et al*., 2024).

MCI, in particular, is an intermediate stage characterized by cognitive complaints, yet with the preservation of basic activities of daily living (ADLs). The conversion rate from MCI to dementia is estimated to be between 10% and 12% per year, compared to 1% to 2% in cognitively healthy individuals (Oliveira *et al*., 2015). In this way, appropriate monitoring of these patients can facilitate the early detection of symptom progression, enabling more timely and effective interventions.

Considering the complexity of the biological data involved, many researchers have adopted advanced technologies, such as Artificial Intelligence (AI), to predict how patients with MCI will evolve over the years (Abe *et al*., 2022; Ghafoori; Shalbaf, 2022; Morabito; Leracitano; Mammone, 2023). AI has proven to be promising in analyzing large volumes of data, facilitating the processing of information obtained from examinations such as magnetic resonance imaging (MRI) and positron emission tomography (PET). This enables the resolution of classification and prediction problems often encountered in data extracted from physiological variables (Cao *et al*., 2023; Ibrahim *et al*., 2021).

AI, a domain of computer science, seeks to create systems capable of replicating the human ability to recognize and analyze problems (Lobo; Lamurias; Couto, 2017). Machine learning (ML) is a subarea focused on pattern recognition through specific algorithms that assist the computer's learning (Russell; Norvig, 2016). Various studies have used ML to detect the conversion from mild cognitive impairment to dementia, primarily to AD (Cai *et al*., 2023; Franciotti *et al*., 2023; Skolariki; Terrera; Danso, 2020). Using different types of inputs for training the models, such as MRI images, PET scans, and demographic and clinical data, research has achieved promising results in accuracy, sensitivity, and specificity, often exceeding 80% (Cai *et al*., 2023; Franciotti *et al*., 2023; Massetti *et al*., 2022; Skolariki; Terrera; Danso, 2020).

This study aims to review, analyze, and synthesize the existing literature on the use of AI in predicting cognitive decline and dementia, identifying challenges and effective methods for applying AI in this context.

METHODS

SEARCH STRATEGY

The search strategy began in May and continued until June 2024, utilizing the PubMed database. The descriptors “dementia”, “prediction”, “artificial intelligence” and/or “diagnosis” were used, as recorded in the Health Sciences Descriptors (DeCS) of the Virtual Health Library (VHL) database, using the boolean operators “and” and “or” to combine the search terms. The selection of studies was facilitated using the Rayyan software developed by the Qatar Computing Research Institute (QCRI).

ELIGIBILITY CRITERIA

The eligibility criteria were employed to reduce the likelihood of bias. Therefore, the inclusion and exclusion criteria corresponding to the PICOS (Population/Intervention/Comparison/Outcomes/Study) framework outlined in Table 1 were followed. Only clinical studies from the last ten years that included the words "dementia", "prediction", "artificial intelligence" and/or "diagnosis" in the title and abstract were considered.

	Inclusion Criteria	Exclusion criteria
Population	Older adults with dementia	Children, teenagers, healthy animals, and neurological diseases (Parkinson's, ALS, Huntington's, multiple sclerosis...)
Intervention/Exposure	Clinical Evaluation, physiological criteria (wearable devices, body temperature, sleep pattern), EEG/MRI/PET scans, and screening tools for clinical applications	Evaluation of a different order
Control	Standard Clinical Examination	-
Results	AI in the prediction/diagnosis of dementia cases	Genetic outcomes
Study (types of studies)	Clinical Trials and Observational Studies	Review; theses; book chapters; editorial; opinion article; letter to the editor

Table 1. PICOS Approach
Source: Authors (2025).

As exclusion criteria, studies that did not clearly describe the ML models employed, as well as those that failed to report key performance metrics in the results — such as accuracy, area under the ROC curve (AUC), sensitivity, specificity, F-measure, and root mean-square error (RMSE) — were excluded.

STUDY SELECTION

The study selection was performed with the aid of the Rayyan tool. The titles and summaries of the articles were evaluated in consideration of their relevance to the topic in question. Two independent researchers (JDOM and MEL) reviewed the studies that followed the previously established inclusion and exclusion criteria. The studies that met the eligibility criteria were evaluated in total. Discrepancies were resolved through discussion between the two independent researchers (APO and TC).

DATA ANALYSIS

Two researchers conducted the synthesis of information extracted from the 17 articles included in the review. Data extraction was carried out using a structured table specifically designed to guide the identification of relevant information in each study. This table systematically organizes the essential elements that characterize the analyzed studies, enabling a comparative overview among them. This systematic method provided a clearer evaluation of the methodological approaches used in the studies.

RESULTS

The review included seventeen articles published between 2015 and 2023, predominantly observational (Figure 1). The studied populations ranged in age from 50 to 85, and the inclusion criteria were based on clinical evaluations. Most studies explored using AI techniques, such as ML and deep learning, to predict neurodegenerative diseases through various clinical assessment tools.

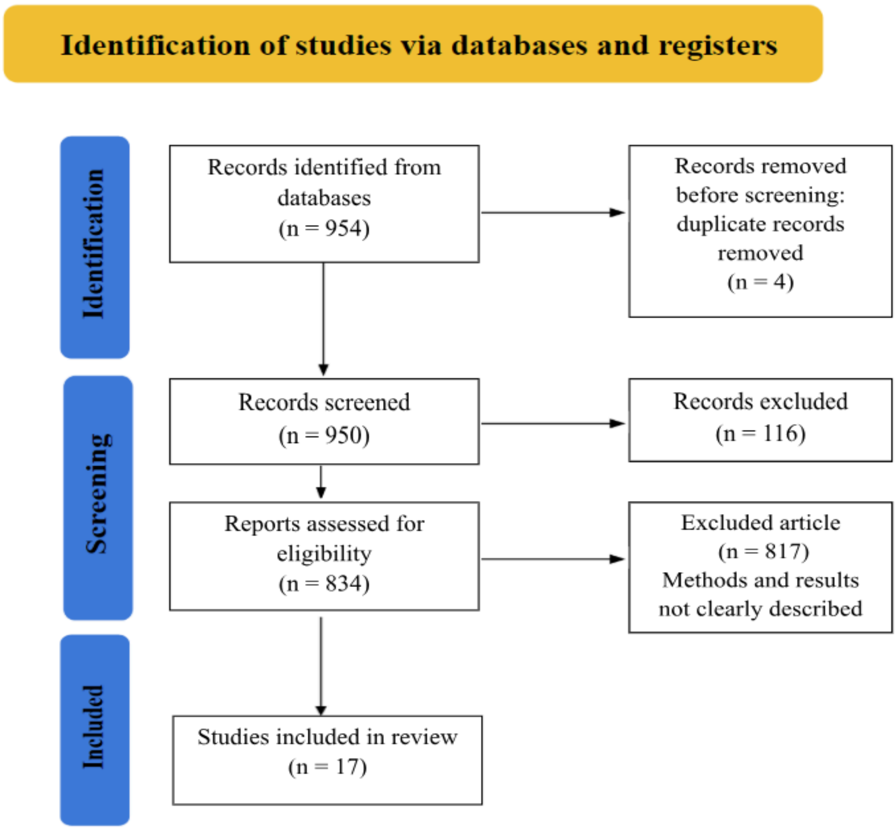


Figure 1. Flowchart of studies included for analysis according to Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Source: Authors (2025).

The studied population included patients diagnosed with AD, MCI, FTD, DLB, and VCI, as well as cognitively unimpaired (CU) individuals (Table 2). There was a considerable variation in the number of participants across studies, which may be attributed to the use of different databases for conducting the experiments. A total of 7.935 patients with various types of cognitive impairment were included in the 17 reviewed studies. For the control group, a total of 4.248 CU individuals were recruited. It was not possible to group patients among the different types of diagnosis, as studies were not always clear regarding the distribution of each type within their sample. Additionally, it was not feasible to stratify the severity of cognitive impairment in patients who had already been diagnosed due to missing data.

Regarding the approach used, nine studies investigated the conversion from MCI to some form of dementia; four analyzed the prediction of beta-amyloid positivity; three employed ML for diagnostic support in distinguishing controls from patients with different types of dementia; and one assessed the cognitive risk in an elderly population.

Author	Country	Design	Participants	Tool group	AI model	VARIABLES/ MODELLING	Main results	Conclusions
Kimura *et al.* (2023)	Japan	Cohort	N = 282 MCI or SCD	Imaging; cognitive tests; biomarkers; physiological data	SVM (Kernel RBF), Elastic Net, Logistic Regression	Models for prediction of amyloid positivity.	AUC 0.70 for lifestyle factors only; AUC 0,79 for wearables + lifestyle factors.	ML models predicted amyloid positivity using non-invasive input.
Pang *et al.* (2023)	USA	Observational	N = 2.349 MCI or AD	Demographic information; lifestyle factors	SVM (Kernel RBF), Random Forest, Logistic Regression	Individuals' baseline characteristics. Info Gain, Chi-square, Fisher, ANOVA	The model predicted conversion from MCI to AD dementia in 2 years with higher accuracy (85%).	The calculator could be used for screening in trials.
Yadgir *et al.* (2022)	USA	RCT	N = 1.736 CU	Cognitive testing data	XGBoost	Cognitive testing with BOMC at the emergency department and health records data.	The model predicted cognitive impairment with AUC 0,72.	An algorithm can identify a subset of patients at higher risk of cognitive impairment.
Park (2020)	South Korea	Observational	N = 103 CU N = 74 MCI	Cognitive testing data	TensorFlow and Logistic Regression	Random data distribution for algorithm training (1) and testing (2).	Mobile screening test system for MCI (mSTS-MCI) was accuracy 96.67% and for MoCA-K was 86.20%.	ML algorithms predict MCI with results comparable to those of conventional screening tools.

Suh *et al.* (2020)	USA	Observational	N = 552 AD N = 743 MCI N = 1.432 CU	Imaging	Linear SVM, Logistic Regression, CCN+XGBoost	Algorithm, using a CNN to perform brain segmentation and classification using a dataset of T1-weighted MRI brain images.	0,98 AUC for AD vs CU 0,80 AUC for AD vs MCI 0,87 AUC for MCI vs CU all with the XGboost model.	The algorithm allowed for an accurate AD diagnosis using T1-weighted brain MRI with the XGboost.
Moscoso *et al.* (2019)	Spain	Observational	N = 230 CU N = 579 MCI N = 230 AD	Imaging	Logistic Regression	Models evaluating the volume of the hippocampus, the entorhinal cortex, and the combination of both areas in a follow-up of 2 and 5 years.	AUC increased from 74% after 2 years to 80% after 5 years.	The brain volume reduction detected by MRI is a good predictor of conversion from MCI to AD.
Ezzati *et al.* (2020)	USA	Observational	N = 279 AD	Demographic data; APOE status; cognitive assessment and MRI images	Decision Trees and kNN	Training with kNN to identify patients with cognitive decline over 12 months.	The kNN model predicted cognitive decline in 12 months with an accuracy of 61.3%, sensitivity of 65.5%, and specificity of 47.0%.	Predictive models from ML can be used to enhance the power of clinical trials.
Zhang *et al.* (2021)	China	Observational	N = 275 CU N = 413 MCI N = 280 AD	Imaging	CNN, ResNet, DenseNet, and CAM-CNN method	MRI processing through CNN aims at classifying AD and distinguishing between converter and non-converter patients with CCL.	Accuracy of CAM-CNN: 97.35% = AD vs HC; 87.82% = MCI vs HC; 78.79% = converters CCL vs non-converters.	The CAM-CNN extracted detailed features from the MRI, which may facilitate early diagnosis and prediction of AD.

Castellazzi *et al*. (2020)	UK	Observational	N = 33 AD N = 27 VD	Imaging	ANN, SVM and ANFIS	Use of machine learning with MRI and DTI data to classify patients with AD and VC and to assist in predicting AD or VD within up to 3 years.	ANFIS accuracy = 85% in discriminating AD and VD and accuracy = 77% in predicting uncertain cases progressing to AD or VD.	High-resolution MRI and DTI can differentiate between AD and VD and predict the patient's progression early on.
Shafiee *et al*. (2021)	Canada	Observational	N = 312 MCI	MRI; demographic data and cognitive assessment	Random Forest	Prognosis of MCI over 2 and 3 years.	Prediction of cognitive decline in 2 years: accuracy = 77%, in 3 years: accuracy = 74%.	The tool was able to predict cognitive decline over time, potentially increasing the statistical power of clinical trials.
Fristed *et al*. (2022)	UK and USA	Cohort	N = 94 CU N = 106 MCI or AD	Cognitive assessment and narrative recall test	ASRT System, Logistic Regression	Detection of beta-amyloid positivity or cognitive decline through speech analysis.	The ASRT presented an AUC = 0.77 for Aβ positivity AUC = 0.83 for CCL.	The ASRT presented an AUC = 0.77 for Aβ positivity AUC = 0.83 for CCL.
Gao *et al*. (2022)	China	Observacional	N = 53 MCI N = 68 CU	Imaging; cognitive tests	SVM	MRI data and regional homogeneity (ReHo) as biomarkers for MCI.	Accuracy = 68.6% of the SVM for distinguishing MCI from CU.	The SVM applied to MRI data and cognitive assessment identified patterns that may assist in diagnosing MCI.

Harper et al. (2016)	UK	Observational	N = 101 AD N = 28 DLB N = 55 FTD N = 73 CU	Imaging	SVM	SVM to evaluate the diagnostic accuracy of six visual classification scales, predicting the histopathological aspects of dementia.	AUC = 0,86 to 0,97 distinguish each pathological group from controls; AUC = 0.75 to 0.92 for the different comparisons of patient groups.	Using SVM improved diagnostic accuracy by combining the scores from the visual rating scales.
Pekkala et al. (2020)	Finland	Observational	N = 48 CU	Demographic data; vascular risk factors; cognitive performance; APOE genotype and MRI	DSI	Analysis of a multimodal model for detecting amyloid positivity.	The best performance was achieved with the combination of APOE data and MRI, with AUC = 0.82.	The combination of MRI data and APOE genotype effectively detected positivity for amyloid.
Retico et al. (2015)	Italy	Observational	N = 144 AD N = 302 MCI N = 189 CU	Imaging	SVM	Comparison of 3 SVM models using MRI data to differentiate AD from CU and predict the conversion from MCI to AD.	AUC = 88.9% for the discrimination of AD vs CU, using the MRI approach of total gray matter.	The analysis of total gray matter may be more effective for the early prediction of AD than specific regions.
Reith et al. (2021)	USA	Cohort	N = 610 ADNI participants (cognitive status not available)	Clinical, genetic and imaging features	CNN, ResNet-50, and Linear Regression	Models for predicting future amyloid deposition and identifying the highest risk of progression.	The model achieved an RMSE = 0.0339 in predicting future SUVR.	It was able to predict a greater accumulation of SUVR at rates 2 to 4 times higher compared to random selection.

Velazquez *et al*. (2021)	USA	Observational	N = 383 MCI	Demographic data; imaging tests; cognitive tests; APOE	Random Forest	Use of ML to predict conversion of patients with MCI to AD.	The algorithm achieved a high accuracy of 93.6% in predicting the conversion from MCI to AD.	The combination of multimodal data can identify patients at greater risk of developing AD.

Abbreviations: MCI - mild cognitive impairment; SCD - subjective cognitive decline; SVM - support vector machine; RBF - Radial Basis Function; AUC - area under the curve; ROC - receiving operator characteristic; RCT - randomized controlled trial; ML - machine learning; BOMC - Blessed Orientation Memory Concentration; MRI - magnetic resonance imaging; ADNI - Alzheimer's Disease Neuroimaging Initiative; HRV - heart rate variation; VaD - vascular dementia; KNN - K-Nearest Neighbors.

Table 2. Characteristics and summary of the main findings of studies included in the review
Source: Authors (2025).

Based on the content of Table 2, it is observed that the majority of the patient populations included in the studies had a diagnosis of MCI or AD. Thirteen of the reviewed studies adopted an observational study design, primarily focusing on predicting the conversion from MCI to AD or the risk of developing dementia. Significant methodological heterogeneity is evident across the articles, reflecting the broad applicability and diversity of approaches in data processing using ML. It is noteworthy that, even among studies employing multiple approaches with different ML models, shallow learning was the most commonly used technique.

As shown in Figure 2, there was a marked increase in the number of publications starting in 2020, with a peak of five studies in that year. In the preceding years (2015-2019), the number of publications was limited, with no more than one article per year. Following the peak, a slight decline was observed, with four studies published in 2021, three in 2022, and two in 2023. This publication pattern in 2020 may be related to the COVID-19 pandemic period, during which many researchers were able to dedicate more time to scientific writing due to lockdown conditions. Although the number of studies decreased in subsequent years, the data reflect a growing interest in applying ML and deep learning models for predicting cognitive decline.

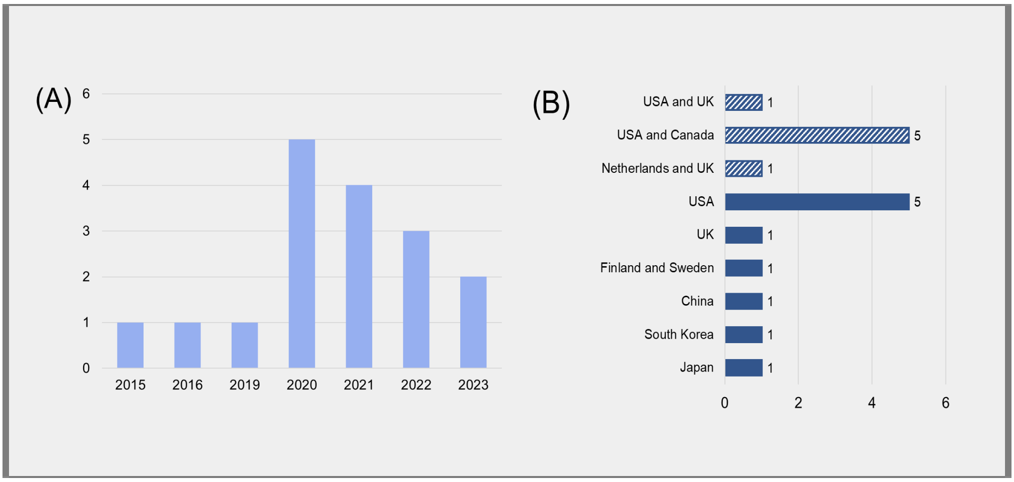
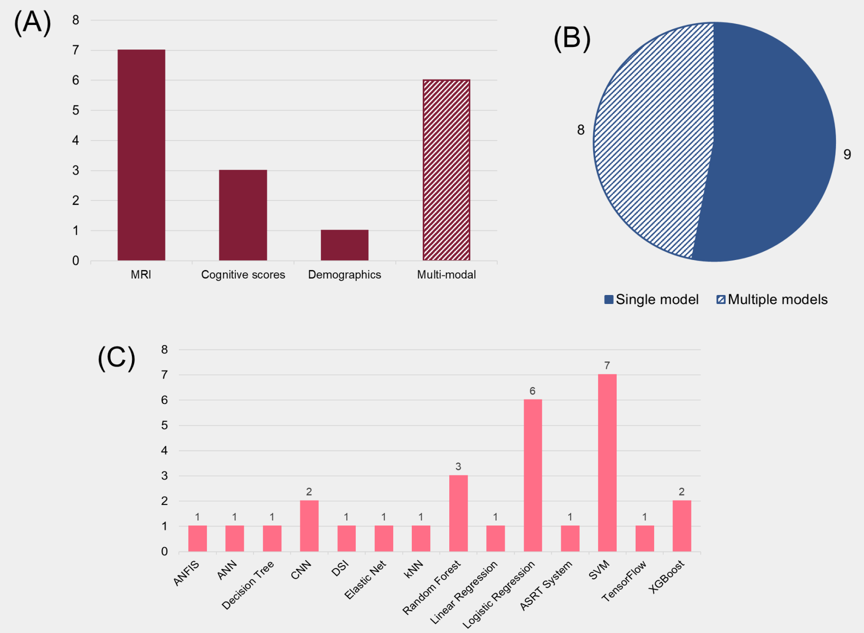


Figure 2. Temporal and geographic characteristics identified among the 17 included studies, in which (A) shows the number of articles published per year and (B) shows the number of articles by country in which the study was conducted
Source: Authors (2025).

The geographical distribution of the included studies is shown in Figure 2, highlighting a predominant concentration in North America. The United States and Canada accounted for the highest number of publications (n = 5 each). Other countries with singular representation (n = 1) include the United Kingdom, the Netherlands, Finland, Switzerland, China, South Korea, and Japan, indicating an international dissemination of interest in the topic, although less pronounced outside the North American axis. Inter-institutional collaborations between countries were also identified, such as those between the United States and the United Kingdom and between the United States and Canada.

Taken together, the temporal and geographical patterns observed indicate a steadily expanding but unevenly distributed research landscape focused on

ML-based prediction of cognitive decline, where regional disparities are remarkable, but scientific interest in the matter continues to grow.



Abbreviations: MRI - Magnetic Resonance Imaging; ANFIS - Adaptive Neuro-Fuzzy Inference System; ANN - Artificial Neural Network; CNN - Convolutional Neural Network; DSI - Disease State Index; kNN - k-Nearest Neighbors; SVM - Support Vector Machine.

Figure 3. Main characteristics regarding input data and ML models identified among the 17 included studies, in which (A) shows the input data used in each study, (B) the number of machine learning or deep learning models applied to interpret data in each study, and (C) the number of studies in which each respective model was used
Source: Authors (2025).

In Figure 3, (A) presents the types of input data used in the studies. MRI data were the most frequently employed, appearing in seven studies, highlighting a trend toward integrating various forms of MRI data processing to enhance predictive accuracy. Multimodal data were used in six studies, while cognitive tests were applied in three. Demographic data alone appeared in only one study, indicating a lower prevalence of this variable as a single input in the models.

Regarding the number of models used per study, (B) shows a relatively balanced distribution: nine studies employed only one machine learning or deep learning model, whereas eight studies tested multiple algorithms for performance comparison.

Finally, (C) illustrates the distribution of the frequency of machine learning and deep learning models used in the analyzed studies. The most frequently used model was the Support Vector Machine (SVM), present in seven studies. Logistic regression was applied in six articles, and Random Forest appeared in three. Convolutional Neural Networks (CNNs) and XGBoost were reported in two studies each. Models such as the Adaptive Neuro-Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN), and Decision Tree were used more occasionally, each in a single study.

Additionally, other specific algorithms — such as Disease State Index (DSI), Elastic Net, k-Nearest Neighbors (kNN), linear regression, the ASRT system, and TensorFlow — were each employed in only one study. These findings indicate a predominance of SVM-based techniques, followed by logistic regression and Random Forest, underscoring a preference for algorithms designed to predict diagnostic categories based on pre-labeled data, that is, models grounded in supervised classification.

DISCUSSION

COGNITIVE ASSESSMENT DATA, SPEECH ANALYSIS, AND DEMOGRAPHIC DATA

Regarding the use of data from cognitive assessments, an overall satisfactory performance of the ML models was observed, with AUC metrics ranging from 0.72 to 0.85. In a North American study, an automated tool was developed and tested for screening cognitive impairment in patients at risk, as seen in an emergency department. The Blessed Orientation Memory Concentration (BOMC) instrument was used as a predictive variable, with the XGBoost model demonstrating the best performance, achieving an ROC curve area (AUC) of 0.72, a sensitivity of 0.73, and a specificity of 0.64 (Yadgir *et al*., 2022).

Following this line, researchers utilized the MMSE (Mini-Mental State Examination) associated with clinical and sociodemographic variables to train ML models in a community cohort, achieving AUCs greater than 0.85 with Random Forest (RF) and Support Vector Machine (SVM) for the detection of mild dementia (Lin *et al*., 2020). The cited studies show methodological differences, with one being a point-in-time assessment of cognitive impairment and the other involving long-term follow-up of a population. This impacted the better performance of the second study.

Another approach utilized two well-known cognitive assessments (mSTS-MCI and MoCA) to process information through the ML model using logistic regression, which was compared to the results of a standard application of the tests. Although the outcome metrics achieved similar values in the comparison, the positive predictive value (PPV) using ML algorithms for identifying patients with MCI was 100%. (Park, 2020). A high PPV can prevent errors in tracking patients with MCI; that is, the system based on the mSTS-MCI was more effective in properly selecting patients with early cognitive impairment. The literature provides similar results, such as the work of Yim, Yeo and Park (2020), who conducted a study involving 955 participants, divided into three groups: healthy individuals, those with MCI, and those with dementia. Different ML algorithms were applied, including logistic regression, to classify participants based on cognitive assessments such as the MMSE and MoCA. The models achieved accuracies ranging from 67.8% to 99.9%, with AUCs superior to those of conventional screening models.

In addition to the data-driven approach, another perspective conducted a discourse analysis of the participants. They used the Story Retention Analysis Test (SRAT) and a cognitive assessment. The participants' responses were transcribed and analyzed using an AI model through logistic regression, which compared the content of the original stories with the participants' recollections. The results demonstrated a detection of mild MCI or AD dementia with an AUC of 0.83 (Fristed *et al.*, 2022). When compared to previous studies, it is possible to note similar performances, such as a research that used story recall tasks via smartphones and reported an AUC of 0.85 for detecting MCI/AD (Chou *et al*., 2024).

Demographic data was also analyzed as an input source in ML models. One study included in the review aimed to predict cognitive impairment using only demographic variables, such as age, sex, education, and income. The results showed limited performance, with models based solely on this data achieving an accuracy of less than 70% and AUC values between 0.60 and 0.68, indicating modest discriminative ability (Pang *et al*., 2023). Another study that investigated the progression from MCI to AD dementia found better performance by incorporating a sociodemographic stratification. The data were classified using a predictive model based on the RF algorithm trained with data from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database. The study included analyses stratified by age and sex, revealing that the model performed better in women and younger individuals, mainly when used in combination with neuropsychological and cerebrospinal fluid data (Massetti *et al*., 2022). The accuracy varied depending on the analyzed subgroups, indicating that demographic characteristics may influence the performance of AI models.

MAGNETIC RESONANCE DATA

Regarding the use of magnetic resonance imaging (MRI) images, the literature reveals significant methodological heterogeneity in studies. This variability is observed both in the types of images used (whole brain, specific segmentations, regional homogeneity) (Castellazzi *et al*., 2020; Retico *et al*., 2015; Suh *et al*., 2020) as well as in comparisons between groups of patients and controls and early identification of markers of cognitive impairment (Gao *et al*., 2022; Harper *et al*., 2016; Moscoso *et al*., 2019). Despite this diversity, there is a prominent and growing application of ML techniques in these contexts, highlighting their potential to explore complex patterns of information.

Research employing MRI analyses often aims to identify areas associated with cognitive decline. In this regard, researchers used the SVM model to predict the progression of MCI and AD dementia. Through a technique called Recursive Feature Elimination, it was possible to identify which parts of the gray matter were most relevant for diagnosis. The model achieved high accuracy, correctly identifying about 90% of cases (Retico *et al*., 2015). This suggests that the analysis conducted by the algorithm may reveal discriminatory patterns that are not initially expected by traditional clinical observation. Similar results were found in a more recent study, such as that of Vichianin *et al*. (2021), who also applied the SVM model to MRI images and reported good performance in differentiating between healthy individuals and those with AD.

Additionally, other approaches to MRI processing are reported in the studies, such as segmentation analysis, targeting regional metrics in MRI images, extraction of three-dimensional spatial features, and analysis of regional homogeneity (Castellazzi *et al*., 2020; Gao *et al*., 2022; Suh *et al*., 2020; Zhang *et al*., 2021). Despite the different methods used, the results of the final classification are satisfactory, with accuracy values between 64% (SVM model, classification between MCI vs CU) (Gao *et al*., 2022), 84% (ANFIS model, classification between AD vs VCI) (Castellazzi *et al*., 2020) and 97% (CAM-CNN model, classification of AD vs CU) (Zhang *et al*., 2021). Moreover, another study achieved a result of 0.95 in the AUC (XGBoost model, differentiation between AD vs CU) (Suh *et al*., 2020).

Current literature supports the increasing use of algorithms for risk stratification and amyloid positivity prediction, especially in cognitively healthy populations or in patients at early stages of cognitive impairment. One study identified brain atrophy, which was associated with the presence of amyloid deposits, with an AUC of up to 0.80 after 5 years of follow-up, using a logistic regression model (Moscoso *et al*., 2019). In a complementary manner, a study conducted a comparison of structural MRI images and post-mortem histopathological diagnoses to identify, using the SVM model, the pathological prediction in patients with dementia vs CU. The model achieved an AUC between 0.86 and 0.97 in the classification between controls and patients and an AUC of 0.75 and 0.92 in differentiating between types of dementia (Harper *et al*., 2016). These findings align with the literature, as a study utilizing structural MRI data successfully predicted beta-amyloid positivity in individuals with MCI. The SVM model demonstrated promising performance in positivity classification, with an AUC of 0.89 (Kang *et al*., 2021).

MULTIMODAL DATA

In a series of studies focused on constructing predictive models for neurodegenerative diseases, multimodal approaches stand out, integrating various types of data. Considering the biological heterogeneity that characterizes these diseases, the use of multimodal data in conjunction with machine learning emerges as a differentiated evaluation strategy, encompassing everything from imaging exams to lifestyle-related information.

Among the studies analyzed, those that integrated clinical data with structural neuroimaging stand out. Shaffie *et al*. (2021), for example, combined cognitive data (MoCA, ADAS13, MMSE, RAVLT) with imaging biomarkers (SNIPE scores for the hippocampus and entorhinal cortex), achieving an accuracy of 76.9%. Likewise, Ezzati *et al*. (2019), using a robust methodology, analyzed different sets of variables (MRI, demographic, and genetic data), achieving an accuracy of 92.8%.

A North American study addressed nine clinical variables, including genetic biomarkers (APOE4), imaging biomarkers (hippocampal volume and lateral ventricle volume), cognitive tests (ADAS13, ADAS11, MMSE, FAQ), and demographic data, achieving an accuracy of 93.6%, standing out as the best performance among the analyzed studies (Velazquez; Lee; Alzheimer’s Disease Neuroimaging Initiative, 2021). Among these models, Shafiee *et al*. (2021) stands out for its greater accessibility, since it maintains good performance even when using cognitive data that is easily accessible in clinical practice. Despite the technical demands of the SNIPE score derived from MRI, the authors argue that the model still presents satisfactory results with isolated cognitive data. In contrast, the other studies, although with high accuracy, require more specialized resources, such as brain image segmentation, genotyping, and extraction of complex structural biomarkers.

It is essential to highlight that, despite the studies using different models and participants, the integration of multimodal data yielded efficient parameters, demonstrating a robust predictive strategy. Moreover, reports from El-Sappagh *et al*. (2021) and Li, Lian and Vardhanabhuti (2025) corroborate the accuracies mentioned above, achieving, respectively, 94.4% accuracy and an AUC of 0.81, using different input datasets, ranging from clinical and imaging data to genetic and lifestyle information.

Researchers have developed a multifactorial predictive model aimed at detecting the presence of beta-amyloid in elderly individuals at high risk of dementia but still without evident clinical signs. The integration of genetic (APOE ε4), neuropsychological, clinical, and structural MRI data revealed that medial temporal lobe atrophy, combined with genotyping, provided superior performance (AUC = 0.82) compared to models based solely on demographic or vascular factors

(Pekkala *et al.*, 2020). The early identification of beta-amyloid positivity in still asymptomatic populations proves to be strategic, as it enables more sensitive clinical monitoring and facilitates more effective interventions.

Another study included in the review demonstrated that deep learning models, integrating CNN (ResNet-50) and gradient boosting decision trees (GBDT), were effective in predicting future beta-amyloid deposition, showing a relatively low error (RMSE = 0.0339). This approach substantially enhances the early identification of individuals with rapid disease progression, which represents a strategic contribution to optimizing participant selection in clinical trials, especially in the early stages of the disease (Reith; Mormino; Zaharchuk, 2021).

The study published by Palmqvist (Palmqvist *et al.*, 2019) contributes to this perspective, as it associates beta-amyloid data with cognitive data, achieving an AUC of 0.81 in the prediction of amyloid deposition. Similarly, a recent study obtained satisfactory results by combining demographic and imaging variables (T1, T2-FLAIR, and αPET), reaching an AUC of 0.94 (Lee *et al.*, 2024). Despite the methodological differences among the studies analyzed, a consistent trend of positive results is observed in the predictive aspects, particularly regarding the use of beta-amyloid as a biomarker to estimate the risk of conversion from MCI to AD. The articles differ in both the types of data used and the computational models adopted, which highlights the flexibility and broad applicability of ML-based approaches in this context.

In Kimura's study, an association was conducted between data from wearable sensors (activity, sleep, heart rate, and conversation time) and questionnaires about lifestyle and social environment, as well as demographic data, MoCA-J, and PiB-PET (Kimura *et al*., 2023). The best performance was achieved with the complete set (sensors, lifestyle, and demographic data), reaching an AUC of 0.79. With the addition of MoCA-J, the value increased to 0.83, demonstrating an efficient model even without the use of neuroimaging as input data. By using accessible resources, the model shows potential for broader implementation. However, the absence of direct pathophysiological data limits its predictive capability at more specific stages of the disease, as these variables are indirectly associated with the clinical condition.

Additionally, the importance of carefully selecting variables stands out. Shafiee *et al*. (2021) included the RAVLT test in their model, while Velazquez, Lee and Alzheimer’s Disease Neuroimaging Initiative (2021) chose to exclude it after finding that its inclusion reduced the accuracy of the model. This fact demonstrates that not every clinically valid variable is necessarily generalizable to predictive models. It becomes essential to test its contribution in different contexts empirically and to use evidence from the literature as support for optimizing model performance.

The present study had limitations, including difficulty in selecting articles, as many titles did not accurately reflect the investigated content, which complicated the initial screening process. Additionally, some studies had gaps in their methodological procedures and presentation of results, which led to their exclusion from the literature synthesis process. These limitations underscore the need for future research to employ more robust methodologies, with a clear description of the designs used and the outcomes observed.

Although some studies reported accuracy values exceeding 90%, it was observed that comparisons between patients already diagnosed with AD and healthy controls yielded the best performance. In contrast, analyses involving patients with MCI and controls tend to show lower accuracy, limiting the applicability of these models in this highly relevant population. The use of diverse ML models also contributes to substantial methodological heterogeneity, hindering direct comparisons across studies. Collectively, these factors undermine the generalizability of the models in real-world clinical settings aimed at screening for cognitive impairment.

CONCLUSION

This research demonstrated that the use of different ML models serves as an aid for diagnostic investigation for various cases of dementia syndromes. Additionally, applications involving multimodal datasets, especially those incorporating MRI examinations, enhance the overall performance of the models, with this approach considered one of the most effective. The use of more widely accessible data, such as demographic information, also showed satisfactory outcomes, proving to be a robust approach for ML processing.

Thus, future research directions should prioritize the inclusion of easily accessible and relatively low-cost data, such as sociodemographic information, in models for predicting cognitive impairment. This approach is particularly relevant for developing countries, such as Brazil, which is undergoing rapid demographic transition and requires accessible and effective screening tools.

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