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Artificial Intelligence for Detection of Dementia Using Motion Data: A Scoping Review

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Keywords
Artificial intelligence · Dementia · Machine learning · Screening · Detection · Motion tracking

Abstract

Background: Dementia is a neurodegenerative disease resulting in the loss of cognitive and psychological functions. Artificial intelligence (AI) may help in detection and screening of dementia; however, little is known in this area. ***Objectives:*** The objective of this study was to identify and evaluate AI interventions for detection of dementia using motion data. ***Method:*** The review followed the framework proposed by O'Malley's and Joanna Briggs Institute methodological guidance for scoping reviews. We adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) checklist for reporting the results. An information specialist performed a comprehensive search from the date of inception until November 2020, in five bibliographic databases: MEDLINE, EMBASE, Web of Science Core Collection, CINAHL, and IEEE Xplore. We included studies aimed at the deployment and testing or implementation of AI interventions using motion data for the detection of dementia among a diverse population, encompassing varying age, sex, gender, economic backgrounds, and ethnicity, extending to their health care providers across multiple health care settings. Studies were excluded if they focused on Parkinson's or Huntington's disease. Two independent reviewers screened the abstracts, titles, and then read the full-texts. Disagreements were resolved by consensus, and if this was not possible, the opinion of a third reviewer was sought. The reference lists of included studies were also screened. ***Results:*** After removing

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duplicates, 2,632 articles were obtained. After title and abstract screening and full-text screening, 839 articles were considered for categorization. The authors categorized the papers into six categories, and data extraction and synthesis was performed on 20 included papers from the motion tracking data category. The included studies assessed cognitive performance (n = 5, 25%); screened dementia and cognitive decline (n = 8, 40%); investigated visual behaviours (n = 4, 20%); and analyzed motor behaviors (n = 3, 15%). ***Conclusions:*** We presented evidence of AI systems being employed in the detection of dementia, showcasing the promising potential of motion tracking within this domain. Although some progress has been made in this field recently, there remain notable research gaps that require further exploration and investigation. Future endeavors need to compare AI interventions using motion data with traditional screening methods or other tech-enabled dementia detection mechanisms. Besides, future works should aim at understanding how gender and sex, and ethnic and cultural sensitivity can contribute to refining AI interventions, ensuring they are accessible, equitable, and beneficial across all society.

Introduction

The National Institute on Aging (NIA) defines dementia as "the loss of cognitive functioning – thinking, remembering, and reasoning – and behavioral abilities to such an extent that it interferes with a person's daily life and activities" [1]. According to the NIA, the functions affected by dementia include but are not limited to memory, language skills, visual perception, problem solving, self-management, and the ability to focus and pay attention. Some people with dementia cannot control their emotions, and their personalities may change [1]. To date, no treatment has been discovered to cure dementia or reverse its effects. Ongoing research focuses on slowing down the progression of the disease. In Canada, in 2020, there were approximately 597,000 individuals living with dementia and in 2030 that number is projected to increase to 955,900 [2]. Therefore, it has become increasingly important to detect dementia at its early stages to prevent the patient's cognitive function from further declining. This also gives the patient and their loved one's time to prepare for the future and make the proper arrangements.

Artificial intelligence (AI) is defined by John McCarthy as "the science and engineering of making intelligent machines," and has become an integral part of medicine, both in detection and treatment [3]. This can be seen in many areas of medicine, for example, cardiology [4] and radiology [5]. AI was first implemented in heart disease to improve drug therapy by finding effective treatment options with minimal side effects [6]. Since then, AI has also been instrumental in improving cardiovascular imaging, phenomapping, and drug research [7]. AI has also become an integral part of treating diabetes, specifically with regards to diabetic retinopathy, which causes secondary blindness [7]. Scientists and clinicians have been able to design a deep-learning model that is able to diagnose patients with sensitivity and specificity of over 90% that can analyze images of eyes taken by a retinal camera [7]. These advancements are linked to the improvement in AI algorithms such as deep-learning methods, seen in recent years, the increase in access to larger databases, as well as increase in computational power [8].

As AI continues to improve and expand, so has its use in the detection and the identification of a specific condition or disease, such as dementia. One study used AI to track pauses and hesitations from speech recordings, which are common among dementia patients [9]. AI has also become an integral part of the detection process, as new technologies are now capable of analyzing brain images, such as magnetic resonance images (MRI) and positron emission tomography (PET) scans.

Recent studies have been harnessing the power of AI and analyzing motion data to detect dementia, yielding promising and efficient results. One study created a system which can be used to screen out older adults that likely have dementia using machine learning to analyze motion sensor data obtained from a smart home environment [10]. This study concluded the movement trajectories of older adults with dementia differ from those of elders without dementia. [10]. Another study done in South Korea highlights the advantages to using motion sensor data, such as accurate detection, the fact that it is non-invasive, easy to install, comfortable for patients to use as a long-term monitoring system, and that it is affordable for the older adult population [11]. Recently, researchers in Japan used typical activity patterns taken from multiple data sensors to discriminate dementia scores obtained by other dementia screening tests. They found that this easily obtained data have the possibility to estimate the dementia scale score [12]. Therefore, considering the aging population, it is important to provide affordable and non-invasive ways to detect dementia, a goal that motion data is showing promise in achieving.

Despite various possibilities on use of different datasets and modalities, previous literature reviews primarily emphasize on use of AI for diagnostic and prognostic neuroimaging in dementia [13]. We also see this in a methodological review published in 2019 written by Ahmed et al. [14]. According to the study, previous reviews

had a history of concentrating solely on a certain modality, i.e., image modality like MRI or PET, or on a particular type of dementia, like Alzheimer's disease [14].

In recent years, there has been a surge of research in the neuroimaging domain, and our comprehensive review systematically examines the evidence on the use of AI to map out existing knowledge in the field with regard to motion data, which is being studied recently and is showing much room for advancements. Our paper also differs from others by highlighting important ethical and legal aspects in the literature, which were not performed in previous reviews.

While our study screened papers addressing the detection of various types of dementia using a multitude of information sources, such as neuroimaging, the use of senses (audio/speech, olfactory) motion data including eye movement, clinical data (neuropsychological assessment, emergency medical records, questionnaires), biomarkers (blood and plasma, genetics, cerebrospinal fluid), or a combination of these categories. We ultimately decided to focus on the motion category. Therefore, we performed an in-depth review centered around the detection of dementia using motion data, including but not limited to eye movements and wandering patterns.

This scoping review aimed to identify AI-based interventions that have been tested/implemented in the detection and/or prognosis of dementia and assess barriers, facilitators, and outcomes for the use of AI in the detection and/or prognosis of dementia.

Specifically, our research questions were to determine the following:

1. What types of AI interventions using motion data have been tested/implemented in the detection and/or prognosis of dementia?
2. What are the effects of these AI interventions using motion data on outcomes related to health care system and individuals (i.e., patients, health care providers), including psychological outcomes, health behaviors, quality of life, and adverse effects?

Methods

Study Design

Using the scoping review methodological framework proposed by O'Malley's [15] and the Joanna Briggs Institute (JBI)'s methodological guidance for scoping reviews [16], we developed a protocol with the following steps: (1) we clarified the purpose and linked it to two main research questions; (2) we identified relevant studies, which followed the inclusion criteria; (3) we used a team approach with two reviewers to study selection and data extraction; (4) we charted the extracted data; and (5) we collated, summarized, and reported the results. Our protocol is registered and available at the Open Science Framework (osf.io/9rkgw). Lastly, we used the PRISMA-Sc (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) checklist [17] for reporting the results of our review (online suppl. Material 1; for all online suppl. material, see https://doi.org/10.1159/000533693). Studies that did not report their study design were categorized according to their methodology by the classification outlined by the National Center for Biotechnology Information [18]. The screening process is shown in Figure 1 (PRISMA flow diagram).

Eligibility Criteria

We define the eligibility criteria for our strategy using the Population, Intervention, Comparison, and Outcomes (PICO) components [19].

Population

We included all populations who experience the symptoms and loss of cognitive function, who receive and provide dementia care services including holistic post-diagnostic care, as well as family caregivers; all individuals with all types and stages of dementia as stated in condition or domain being studied; and all individuals who receive dementia care. This includes all types and stages of dementia. As stated by the NIH "the causes of dementia can vary, depending on the types of brain changes that may be taking place" [1]. These types include but are not limited to Alzheimer's disease, Pick's disease, Lewy body disease, mild cognitive impairment (MCI), neurodegenerative diseases, frontotemporal disorders as well as other types of progressive brain diseases such as vascular contributions to cognitive impairment and dementia, and mixed dementia, a combination of two or more types of dementia. We excluded Parkinson's and Huntington's diseases.

Intervention(s), Exposure(s)

Studies focused on the testing and/or implementation of AI interventions using motion data were included. We included all methods such as computer heuristics, expert systems, fuzzy logic, machine learning methods such as support vector machine (SVM), Bayesian network, Bayes network, and neural network (NN), knowledge representation, automated reasoning. Studies using the following methods/data to detect dementia were excluded: brain scans such as MRI, PET, single photon emission computed tomography, electroencephalogram, functional near-infrared spectroscopy, magnetoencephalogram, optical coherence tomography retinal scan; clinical data; senses data including audio/speech; biomarkers such as blood and plasma, genetics, cerebrospinal fluid; or a hybrid approach including one or more of these categories.

Comparator(s)/Controls

We included studies with or without comparison groups and head-to-head interventions.

Outcomes

The primary outcomes of interest were those related to patients, health care providers, and the health care system.

Study Selection Process

Protocol

Our protocol was developed using the template of the scoping review protocol by Joanna Briggs Institute framework [16]. The protocol is available in Open Science Framework (osf.io/9rkgw).

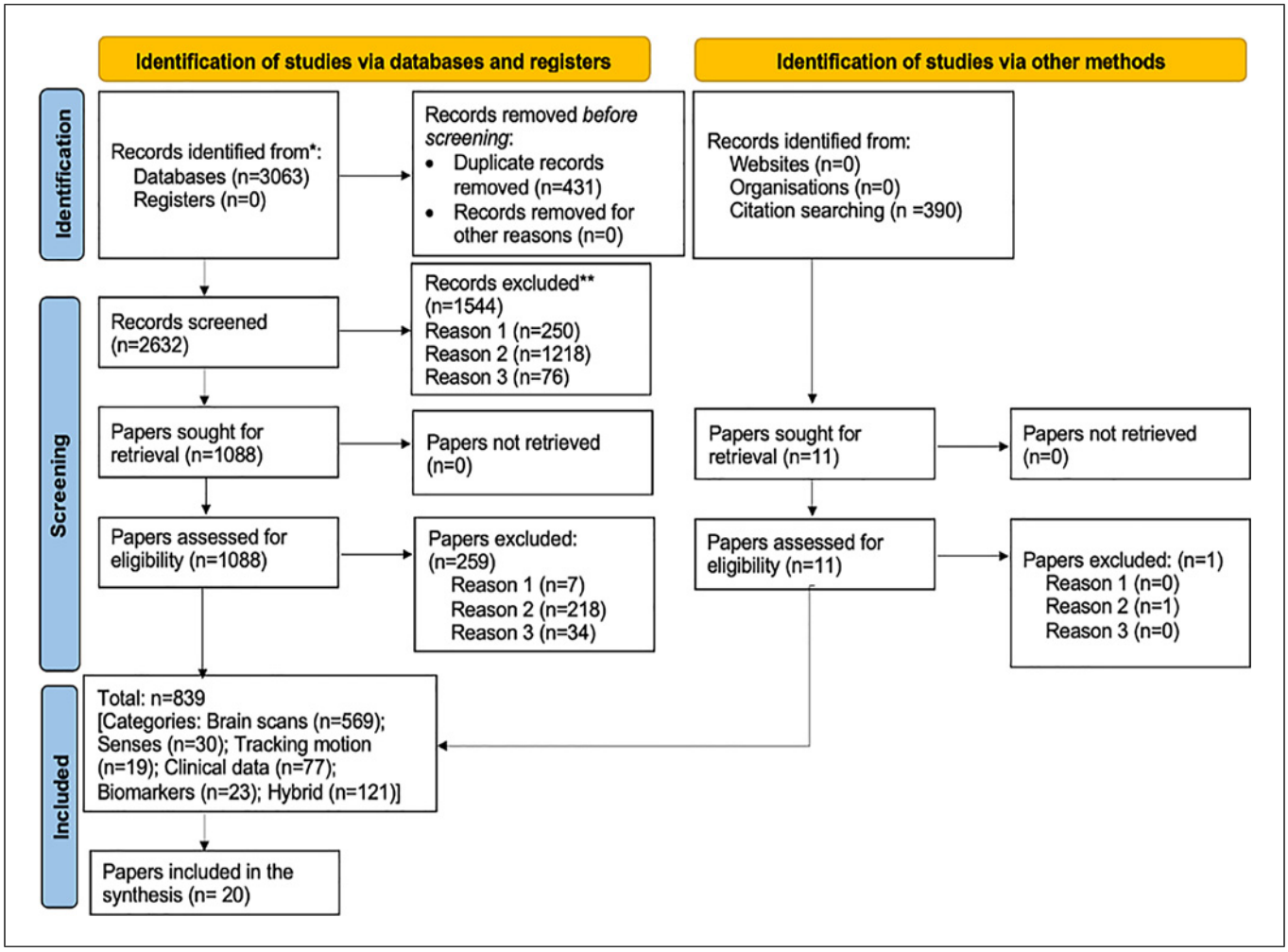

Fig. 1. PRISMA flow diagram.

Search Strategy

An experienced information specialist (G.G.) designed our search strategy, which involved comprehensive searches of the following databases: MEDLINE, EMBASE, Web of Science Core Collection, CINAHL, and IEEE Xplore. The searches were conducted from the date of inception to November 2020. Hand search of reference lists of included papers was also performed to identify additional relevant studies.

Study/Source of Evidence Selection

Search results and inclusion criteria were uploaded to the online systematic review software DistillerSR. The inclusion criteria were used for both level 1 screening of titles and abstracts and level 2 screening of full-texts. The inclusion criteria for the study selection were based on the following questions: (1) Does the study involve an AI intervention using motion data? (2) Does the study focus on the detection of dementia-related conditions, including Alzheimer's disease, Pick's disease, Lewy body disease, MCI, frontotemporal disorders, vascular dementia, primary progressive aphasia, or cognitive dysfunction/decline? The article was excluded from the analysis if it was a review, opinion piece, editorial, comment, news, or letter.

Title and Abstract Screening (Level 1)

Two independent reviewers (L.P.S. and J.K.) screened the titles and abstracts of all retrieved references on DistillerSR software. A questionnaire based on the existing eligibility criteria was used in the screening process. In addition, papers that were not in English were excluded. In cases of disagreements between the two reviewers regarding selection, a third reviewer was consulted to resolve the conflict (S.A.R.). Once the two reviewers confirmed the eligible studies, the reference was selected for full-text screening (level 2).

Full-Text Screening (Level 2)

At this level, the same two reviewers (L.P.S. and J.K.) independently reviewed the full-texts selected at level 1 for their eligibility to be included in the review. The standardized questionnaire based on the existing eligibility criteria was again used in

DistillerSR software, and a third reviewer (S.A.R.) resolved inclusion conflicts. Studies that met eligibility criteria were included for data extraction.

Data Charting, Analysis and Presentation

To extract data, we designed a form derived from the Cochrane Effective Practise Organisation of Care Review Group (EPOC) data collection checklist. The data extraction form was approved by a multidisciplinary group of experts, including health care providers. Extracted data included study characteristics split into four groups: population, intervention, comparison, and outcome. Characteristics such as country of research, study design, population characteristics including the number of participants, nature of condition or illness; intervention characteristics such as AI techniques used; and outcome characteristics including outcomes related to patients, health care providers, and the health system were extracted. The same two reviewers extracted data. A pilot study was conducted with the team prior to charting until sufficient agreement was achieved. All discrepancies were resolved by a third reviewer.

We performed a descriptive synthesis. The tools and techniques for synthesis included textual descriptions of studies, plot groupings and clusters, and tabulation. As recommended in the Joanna Briggs Institute guide [16] a risk of bias appraisal was not conducted.

Results

We identified 2,632 non-duplicate records for preliminary screening of titles and abstracts. Of these, 1,099 studies met the eligibility criteria and were full-text reviewed. Finally, 839 studies were included for categorization. We categorized these studies into brain scans, senses, motion tracking, clinical data, biomarkers, and hybrid. We only focused on the 20 included papers which used motion tracking. Our study focused on the motion tracking category as previous studies in this field have heavily focused on other categories such as brain scans and biomarkers. New studies show that AI systems could extract useful features from motion sensors [10]. These 20 papers, in which 1 of the 20 was a combination of motion sensor data and other data (hybrid), underwent full data extraction (Fig. 1, PRISMA flow diagram).

Study Characteristics

Countries and Publication Dates

The most represented country was the USA (n = 9, 45%), followed by Taiwan (n = 3, 15%). The remaining 8 studies were from the UK (n = 2, 10%), Canada (n = 1, 5%), the Republic of Korea (n = 1, 5%), Italy (n = 1, 5%), India (n = 1, 5%), Iran (n = 1, 5%), and Brazil (n = 1, 5%). In terms of continents, 50% were done in North America, 30% were done in Asia, 15% were done in Europe, and 5% were done in South America. The year of publication ranged from 2011 to 2020.

Methods of Recruitment and/or Datasets Used

The most commonly used datasets were private datasets (n = 9, 45%), and the two most common types of private data were the Emory Healthy Brain Study/Goizueta Alzheimer's Disease Research Center data (n = 2, 22%) and the Oregon Center for Aging and Technology database (n = 2, 22%). Following this were public datasets (n = 4, 20%) and electronic health records data (n = 4, 20%). Three papers (15%) did not report the dataset used in their study.

Design of Study and Duration of Study

All studies included in this review were cohort studies. Most of the studies did not include any information regarding the duration of the study (n = 9, 45%). Of those studies that did report, the most common duration was less than 1 month (n = 5, 25%). The second most common durations were between 1 month and 1 year (n = 3, 15%) and more than 1 year (n = 3, 15%).

Number of Participants

Of the 20 included studies, 19 (n = 19, 95%) included information regarding the number of participants. The total number of participants across these studies was 3,100, and the range in the number of participants varied from 12 to 606 participants.

Age of Participants

Of the 20 studies, 7 (n = 7, 35%) did not include specific information regarding the age of the participants. The overall average age of all participants was 70.3 ± 7.9. For participants classified as patients with a neurological disorder, the average age was 71.5 ± 7.3 years and for the control group (healthy participants), the average age was 67.3 ± 7.6 years. No information was provided relating to health care providers age.

Sex and Gender of Participants

Out of the 20 studies, only 12 of them (n = 12, 60%) reported sex of participants. Most of the participants in these 12 reported studies were female (64.7%). No information was disclosed concerning the sex and gender of health care providers or gender of the patients in any of the included studies.

Race of Participants

Only two out of 20 included studies (n = 2, 10%) mentioned the race of participants in their study. Both of these studies reported a predominantly Caucasian participant population, as indicated in Table 1, 2.

Table 1. Race characteristics of study 1 [20]

Race	Tablet (patient set 1), *n* (%)	Eyetribe (patient set 2), *n* (%)
Caucasian	199 (79.6)	274 (90.7)
African American	41 (16.4)	20 (6.6)
Asian	8 (3.2)	4 (1.35)
Other	2 (0.8)	4 (1.35)

Diseases Classification

Among the participants, the commonly mentioned diseases were multiple dementia diseases, accounting for 40% (n = 8, 40%) of the included studies. MCI was the second most common, observed in 25% (n = 5, 25%) of the studies. The remaining 35% of the studies (n = 7, 35%) discussed various illnesses, including dementia (type unspecified) in 20% (n = 4, 20%) of the studies, Alzheimer's disease in 10% (n = 2, 10%) of the studies, and posterior cortical atrophy and young onset alzheimer's disease in 5% (n = 1, 5%) of the studies.

Among the 20 included studies, some included two different types of illnesses. Four studies included both MCI and Alzheimer's, three studies included both MCI and dementia, and one study included both dementia and Alzheimer's disease.

Comorbidities

Out of 20 included studies, 18 did not mention any comorbidity. One study (n = 1, 5%) mentioned the presence of well-controlled chronic diseases, and the other study (n = 1, 5%) mentioned the presence of posterior cortical atrophy.

Other Treatments

None of the included 20 studies mention the presence of any other treatments.

Information Collected from Participants

The two most common pieces of information collected from the participants were their education (n = 3, 15%) and type of home (n = 3, 15%). The third most collected information was the patients' cognitive score (n = 2, 10%). This was assessed using tests including the Mini-Mental State Examination (MMSE), as well as the Cognitive Abilities Screening Instrument (CASI) and the Montreal Cognitive Assessment (MoCA). The MMSE and MoCA assessments are scored between 0 and 30, where results lower than 24 indicate memory impairment. The CASI is scored from 0 to 100, and a score of less than 80 indicates an impairment of cognitive abilities. The other types of information collected were driver's license (n = 1, 5%), their dexterity, specifically being right-handed (n = 1, 5%), history of substance abuse or learning disability, dementia, neurological or psychiatric illness (n = 1, 5%), use of assistive devices, such as a walker or a wheelchair (n = 1, 5%), height and weight (n = 1, 5%).

Missing Data

In 50% of the studies (n = 10, 50%), it was not explicitly stated whether missing data existed. Among the remaining 50% of studies that addressed missing data (n = 10, 50%), nine studies (n = 9, 45%) chose to exclude the missing data from their analyses. However, one study (n = 1, 5%) chose a different approach and handled the missing data by analyzing the percent of missing data from dementia patients when tested versus healthy patients. Specifically, they input the missing data as a value of 0, as this missing data may be representative of fatigue or cognitive load, which was relevant to the results of their study.

AI Methods Used

The most common type of AI methods used were hybrid methods (n = 9, 45%) which combine two or more machine learning and/or soft computing methods for higher performance and optimum results. The second most common type used were neural networks (n = 6, 30%). Following this, the other types were Bayesian networks (n = 1, 5%), machine learning classification model, however; the exact method was not specified (n = 1, 5%), generalized linear model (n = 1, 5%), and logistic regression (n = 1, 5%). The hybrid methods included the following:

- Support vector machines (SVMs) and Random forest (RF)
- SVM and Gradient Boosted Trees (XGBoost)
- K-nearest neighbors (KNN), logistic regression, SVMs, RF
- Logistic regression and RF
- RF, logistic regression, SVMs, and Bayesian networks
- SVM, RF, and Neural network (NN)
- Naïve Bayes, logistic regression, and SVM
- Naïve Bayes, decision tree (J48), sequential minimal optimization, and NN

A plot is provided (Fig. 2, Map of included studies) to illustrate the variety of AI methods utilized, alongside the respective publication years of the studies employing these methods.

Table 2. Race characteristics of study 2 [21]

Race	Controls (n = 182, 61.5%)	MCI (n = 74, 25%)	AD (n = 40, 13.5%)
Caucasian	154 (52%)	66 (22.3%)	38 (12.8%)
African American	21 (7.1%)	6 (2%)	2 (0.6%)
North and South American (NA)	1 (0.3%)	2 (0.6%)	0
Asian	4 (1.4%)	0	0
Other	2 (0.6%)	0	0

Data Collection Approach for Model Development

The primary method of data collection used by the included studies was fixed motion sensors (n = 9, 45%). This was closely followed by eye-trackers (n = 6, 30%) and wearable sensors (n = 2, 10%). Other methods of data collection used included the Digiped, i.e., measures angular velocities and accelerations (n = 1, 5%), a tablet (n = 1, 5%), and a driver guidance system that mimics the interior of a vehicle, including the steering wheel, dashboard, mirrors, and seatbelt (n = 1, 5%).

Delivery Mechanism

The majority of the studies applied an algorithm directly to the data (n = 17, 85). Two of the studies used a tablet as an interface device (n = 2, 10%), and one used a computer for this purpose (n = 1, 5%).

Knowledge Generated

We categorized the included studies to four main categories based on the broader aim and the predominant focus of each study. There may be overlaps, as some studies encompass elements pertinent to multiple categories. About 25% of the included studies (n = 5, 25%) focused on cognitive performance assessment. These studies aimed at evaluating cognitive performance using various tools such as mobile applications, sensor-based wearable devices, gait data analysis, and visuo-spatial memory paradigms. Subsequently, a significant portion of the studies, about 40% (n = 8, 40%), focused on screening of dementia and cognitive decline. These studies focused on the early detection and screening of dementia and cognitive impairments using different datasets and analysis such as motion sensor data analysis, inhabitant travel pattern classification, driving data analysis, and smart home data analysis. 20% of the studies (n = 4, 20%) investigated visual behaviours. The main point in these studies was the analysis of visual behavior, especially eye movement metrics, to differentiate between cognitively healthy and impaired individuals, or to understand the association between visual behavior and cognitive status. Lastly, 15% of the studies (n = 3, 15%) analyzed motor behaviors. This includes a spectrum of activities such as general human behavior, in-home activity patterns, and locomotor variability, to facilitate early detection of cognitive impairments and to evaluate the potential use of motion data in dementia research.

Performance of AI Interventions

The mostly used performance matrice used by the papers in this review was Area Under the Curve (AUC) (n = 11, 55%), which had a range of 0.67–0.96. The best score of 0.96 AUC came from a study that used logistic regression and RF model and had a total of 35 participants. The second most used matrice was accuracy (n = 5, 25%) with a range of 66.7–98%. The best score of 96%, came from a study that used a recurrent NN. The other types used were sensitivity (n = 3, 15%) with a range of 85.7–87%, specificity (n = 2, 10%) with a range of 72.7–93%, and F1 (n = 1, 5%). The detailed information on AI interventions is provided in the online supplementary Material 2.

Comparison to an AI Alternative

For nine of the 20 papers, there was no AI alternative to be compared to the original (n = 9, 45%). For the 11 out of the 20 (n = 11, 55%) that authors used an alternative AI method to compare to the original/proposed method, seven used hybrid methods and four did not specify which methods were used.

Comparison to a Non-AI Alternative

Out of the 20 papers, 17 did not have a non-AI alternative (n = 17, 85%) to compare to. The remaining three papers (n = 3, 15%) each presented a distinct non-AI comparison method:

- In one study, AI was compared to handcrafted features which used basic eye movement statistics such as saccade counts, total duration of saccades, fixation counts, to distinguish between healthy individuals and those with dementia [22].

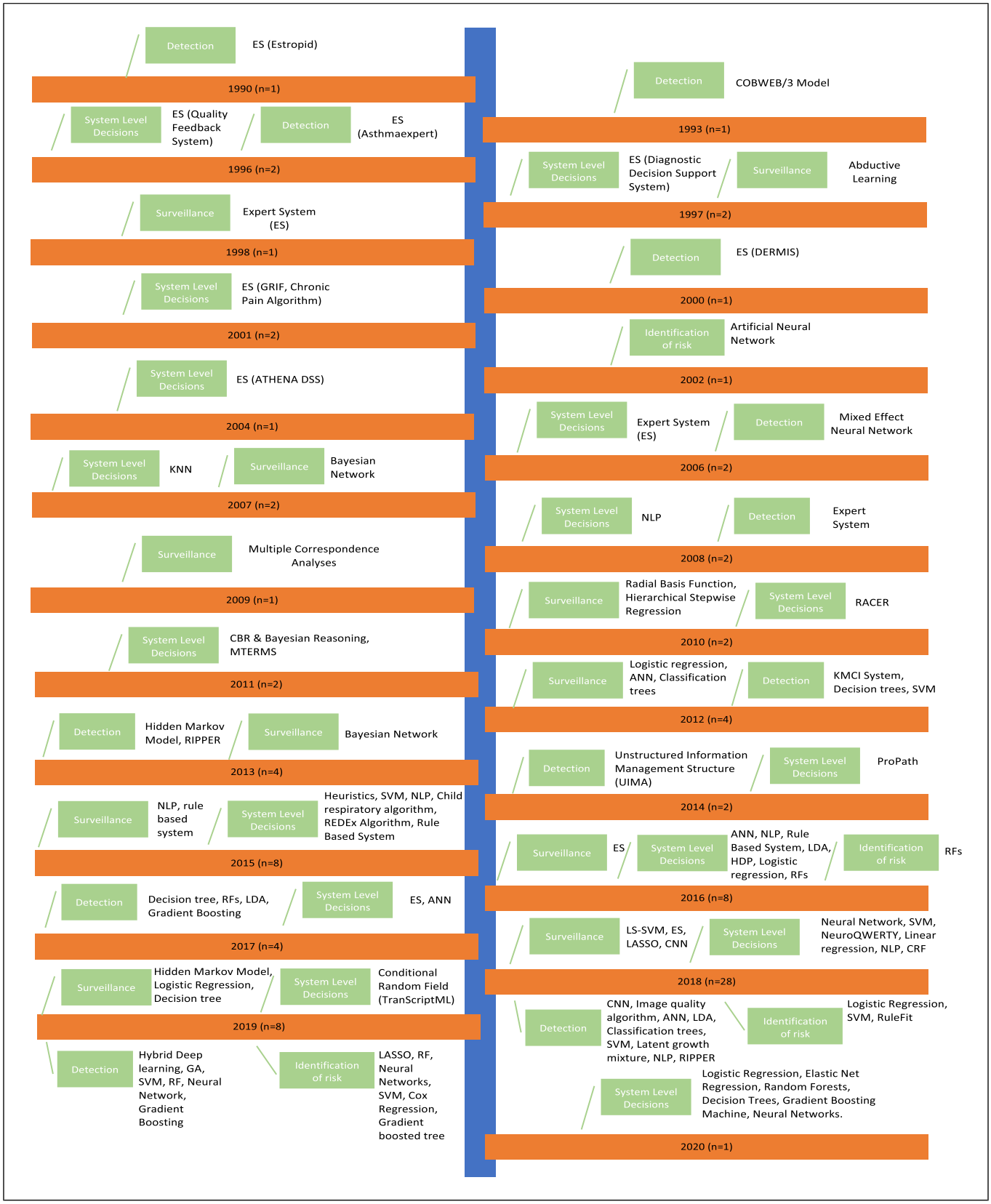

Fig. 2. Map of included studies.

- In another study, AI was compared to the FCSRT scale which identifies mild dementia [21].
- In the other study, AI was compared to the MMSE which is a widely used test of cognitive function among the elderly that includes tests of orientation, attention, memory, language, and visual-spatial skills [23].

Legal Aspects

No legal issues were mentioned in any of the 20 studies. However, few studies (n = 6, 30%) mentioned following aspects: legal guidelines (n = 2, 10%), informed consent from participants (n = 2, 10%), and informed consent and legal guidelines (n = 2, 10%).

Co-Intervention

No co-interventions were stated for any of the studies.

Economic Parameters

The economic parameters were not stated for 17 of the 20 studies (n = 17, 85%). Three of the studies mentioned an interest in creating a low-cost decision algorithm for future projects (n = 3, 15%). However, in these 3 studies, there was no mention of any economic parameters or cost-effectivness analysis in the current project.

Health Care Providers, Patients, and System Outcomes

Out of 20 included studies, 15 did not mention any health care provider-related outcomes (n = 15, 75%). Three of the studies noted that the AI intervention provides a positive diagnostic assistance to health care providers (n = 3, 15%). Two of the studies highlighted that the AI is easily administered and allows for quick screening (n = 2, 10%). Nearly half of the studies, 9 out of 20, did not provide any information regarding the outcomes for the patients. However, some positive insights were gathered from the remaining studies. Three studies (n = 3, 15%) highlighted the benefits of easy, quick, and non-invasive screening methods which enhance the patient experience. One study (n = 1, 5%) pointed out that participants were able to perform the tests without feeling stressed or requiring much assistance. Lastly, about 30% of the studies (n = 6, 30%) emphasized the importance of early detection of dementia that enables timely interventions and offers a proactive pathway to patients to manage the progression of dementia.

Moreover, among the 20 studies included, seven studies (n = 7, 35%) reported that the technology utilizing motion sensors aided in the detection of neurodegenerative diseases while also alleviating the workload of health care providers. Four studies (n = 4, 20%) highlighted its potential in improving widespread screening, and three (n = 3, 15%) emphasized its ease of administration, non-invasiveness, and time efficiency. Two studies (n = 2, 10%) specifically indicated that AI-assisted cognitive assessment provided valuable information. The remaining four studies (n = 4, 20%) did not state any information regarding the healthcare system outcomes.

Discussion

We conducted a scoping review that included 20 studies which were centered around detecting dementia by using motion tracking data such as eye movements and wandering patterns. Our results highlighted an increase in the number of studies since 2015. We observed variability in the reporting participants, type of AI methods, analysis, and the outcomes. Our review leads us to make the following main observations.

Consideration of Age, Sex, and Gender

Out of the included studies, sex, gender, and age were not adequately considered. Out of 20 studies, 19 (n = 19, 95%) reported the sample size. Among those 19 studies, 7 (n = 7, 37%) did not report or clearly report the age of their participants. Among those reported, the mean age of patients was 70.3 ± 7.9 years. According to Shoenmaker et al. [24] study, the average age of participants in dementia research is about 75 years old. However, in the general population, patients who suffer from dementia are around 83 years old. Additionally, older adults below 70 years old are over-represented in dementia research and those above 80, and the ones who suffer directly from dementia are usually under-represented. This trend is followed in our review, in which the 12 studies that reported age had a mean age of 70.3 ± 7.9. This age bias may contribute to a misinterpretation of results and hinder the applicability of findings to the population most affected by dementia, particularly individuals above 80 years old. It is crucial to address this limitation and ensure that future studies encompass a broader age, especially the older population.

Additionally, gender was not at all reported in the studies and sex was only reported in 12 out of the 20 studies, and the majority of the participants were female. According to a study performed at the University of Pennsylvania, it is becoming increasingly important to consider the sex assigned at birth variable [25]. This is due to multiple factors that are very different between females and males such as apolipoprotein E (APOE) genotype, alcohol use, and depression [25]. As illustrated in their

research, females have higher chances of having Alzheimer's, whereas males are more likely to have dementia with Lewy bodies [25]. Additionally, gender plays a role in dementia research [25]. Dementia relies on a multitude of factors including healthy lifestyles and opportunities for advanced education and looking at gender is important in this regard. Our review highlighted a significant gap in AI-dementia research focusing on gender and sex, which can result in under-representation of certain populations and introduce bias when developing AI models. Addressing this gap and incorporating gender as a key variable in future studies and AI development is necessary ensuring an equitable approach in AI-dementia research.

Consideration of Ethnicity and Geographical Location

We also observed that only 10% (n = 2, 10%) of the included studies reported ethnicity and 90% (n = 18, 90%) did not. This was only reported in the patients' category. No data were provided related to ethnicity of health care providers. Among the studies which did report ethnicity of the patients (n = 2, 10%), the patient's data were divided into Caucasian, African American, Asian, and other. However, in both studies that included the data, the vast majority were Caucasian (over 50% and 87% in both respective studies). Recently, a review found that non-Hispanic blacks have roughly double and Hispanics about 50% of the prevalence of dementia compared with non-Hispanic whites in America [26]. The lack of representation of a variety of races in AI-dementia research, especially considering they directly suffer from dementia can cause representation bias, evaluation bias, and algorithmic bias in AI systems. Eventually, the AI system might unintentionally discriminate against marginalized and vulnerable populations, thus concluding with undesirable outcomes.

Moreover, most of the studies in our review were performed in North American and euro-centric settings (e.g., the USA, Canada, the UK). AI has the power to help many people in detecting dementia early; however, the algorithm is only as accurate as the data it is trained with. A big problem with completing the research in resource-rich countries is the fact that this research may not recommend solutions and treatments that are accurate, safe, and fair in low-resource settings [27]. According to the Alzheimer's disease International (ADI) Delphi consensus study, by 2040, 71% of all people with dementia will be living in developing countries [28]. If the algorithm is not trained on fair and diverse data, it is only an advantage to that specific demographic and does not consider how different illnesses affect different populations. The lack of representation will cause representation bias, over-representation and/or under-representation of some characteristics in datasets and in the knowledge base that the AI system is built on, thus amplifying stereotypes and undesirable outcomes. Ensuring an inclusion of more ethnic populations is imperative in avoiding bias.

Ethical and Legal Aspects

Ethical and legal challenges in AI include but are not limited to informed consent to use, safety and transparency, algorithmic fairness and biases, safety and effectiveness, data privacy, and liability [27]. Within our review, only six studies out of 20 included studies (n = 6, 30%) highlighted ethical and legal aspects. These studies primarily focused on adhering to legal guidelines and obtaining informed consent. Therefore, future studies need to delve deeper into these areas to ensure reduced biases and enhanced fairness. There are many ethical questions that must be explored in AI-dementia research [29].

Economical Aspects

In our study, only 3 out of 20 articles mentioned economical aspects. Of these 3, none of them went into depth nor did the cost-effectivness analysis which is a way to assess both the costs and outcomes of one or more interventions. It compares an intervention to another intervention (or the status quo) by estimating how much it costs to gain a unit of a health outcome, like a life year gained or a death prevented. Further cost-effectivness analysis and research are needed to compare the costs and health outcomes associated with the use of AI for early detection of dementia. Seeing as annually dementia costs the Canadian government at least 3.9 billion dollars, this is a necessity step moving forward [30]. Lastly, there is also a need to research how AI will diminish economic costs when it comes to screening and treatment, time, and resource management.

Conclusion

In this scoping review, we demonstrated the extent and variety of AI systems being tested and used in the detection of dementia and demonstrated the potential of motion tracking in this field. Data extraction was performed on 20 studies focusing on AI intereventions using motion data. There is still progress that must be made in development and implmentation of AI systems using motion data for early detection of dementia in pratice, and in building more inclusive systems.

Conflict of Interest Statement

The authors have no known conflict of interest to declare.

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Author Contributions

We reported the contributions according to the CRediT taxonomy. S.A.R. contributed to conceptualization, funding acquisition, project administration, and resources. S.A.R., L.P.S., J.K., and G.G. contributed to the methodology and investigation. L.P.S. and J.K. contributed to data curation. L.P.S. and J.K. contributed to the formal analysis. L.P.S., J.K., and S.A.R. wrote the original draft of this article. H.B., R.G., V.K., G.G., I.V., M.W., N.A., and N.G. contributed to reviewing and editing the article.

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