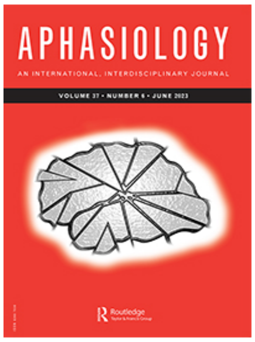

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How artificial intelligence (AI) is used in aphasia rehabilitation: A scoping review

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ABSTRACT

Background: In recent years, artificial intelligence (AI) has become commonplace in our daily lives, making its way into many different settings, including health and rehabilitation. While there is an increase in research on AI use in different sectors, information is sparse regarding whether and how AI is used in aphasia rehabilitation.

Aims: The objective of this scoping review was to describe and understand how AI is currently being used in the rehabilitation of people with aphasia (PWA). Our secondary goal was to determine if and how AI is being integrated into Augmentative and alternative communication (AAC) devices or applications for aphasia rehabilitation.

Methods: Using the Arksey and O'Malley (2005) Levac and colleagues (2010) frameworks, we identified the research question: In what way is artificial intelligence (AI) used in language rehabilitation for people with aphasia (PWA)? We then selected search terms and searched six databases which resulted in the identification of 663 studies. Based on the inclusion criteria, 28 suitable studies were retained. We then charted, collated and summarised the data in order to generate four main themes: (1) AI used for the classification or diagnosis of aphasia/aphasic syndromes or for the classification or diagnosis of primary progressive aphasia (PPA)/PPA variants; (2) AI used for aphasia therapy; (3) AI used to create models of lexicalization; and (4) AI used to classify paraphasic errors.

Results: None of the articles retained incorporated AI in AAC devices or applications in the context of aphasia rehabilitation. The majority of articles (n=17) used AI to classify aphasic syndromes or to differentiate PWA from healthy controls or persons with dementia. Another subset of articles (n=7) used AI in the attempt to augment an aphasia therapy intervention. Finally, two articles used AI to create a model of lexicalization and another two used AI to classify different types of paraphasias in the utterances of PWA.

KEYWORDS
aphasia; rehabilitation; artificial intelligence (AI); communication; scoping review

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Conclusion: Regarding performance accuracy of the diagnosis tools, results show that, regardless the type of AI approach used, models were able to differentiate between aphasic syndromes with a relatively high level of accuracy. Although significant advancements in AI and more interaction between the fields of aphasia rehabilitation and AI are required before AI can be integrated in aphasia rehabilitation, it nevertheless has the potential to be a central component of novel AAC devices or applications and be incorporated into innovative methods for aphasia assessment and therapy. However, for a transition to the clinic, new technologies or interventions using AI will need to be assessed to determine their efficacy and acceptance by both speech-language pathologists and PWA.

1. Introduction

1.1 Background

1.1.1 Aphasia Rehabilitation and Artificial Intelligence (AI)

Approximately one-third of stroke survivors, or more than 100,000 Canadians, live with aphasia (The Heart & Stroke 2017 Stroke Report). As the population ages, this number is expected to double over the next 20 years. While stroke is the most common cause of aphasia in patients seen in rehabilitation it can also accompany traumatic brain injury (TBI) or brain degeneration. While rare, with estimates of its prevalence ranging from 2.7 to 15 cases per 100,000 people, frontotemporal lobar degeneration (FTLD) can result in primary progressive aphasias (PPAs) that have an insidious onset of language deficits that worsen with time. It has been estimated that between 20-40% of people with FTLD have one of the three variants of PPA: the semantic variant (also called semantic dementia), nonfluent agrammatic variant (also called progressive nonfluent aphasia), or logopenic variant (Grossman, 2010).

Living with aphasia can negatively affect a broad range of aspects in the person's life including access to support and health care (Carragher et al., 2021), quality of life (Bullier et al., 2020; Lam & Wodchis, 2010), mental health (Azios et al., 2021; Baker et al., 2020), relationships (Howe et al., 2012), return to work (Graham et al., 2011), and social participation (Dalemans et al., 2010; Le Dorze et al., 2014; Parr, 2007; Simmons & Damico, 2007). This can also affect their communication partner who may avoid communication situations that trigger difficulties. Moreover, family members, and especially spouses, encounter a multitude of problems related to the consequences of aphasia and, the concerns they have about the person with aphasia as well as their unmet caregiving needs (Le Dorze & Brassard, 1995; Le Dorze & Signori, 2010; Michallet et al., 2003). In an attempt to compensate for a person's language impairments and communication difficulties, a number of augmentative and alternative communication (AAC) strategies and systems, ranging from low to high technology, have been developed. In a review of studies investigating the usefulness of high-technology communication aids to enhance communication abilities in adults with aphasia following a stroke, Russo and colleagues (2017) found that individuals generally showed improvement in communication when these technologies were employed. However, they also noted that while the use of such aids could be useful in improving communication and social participation, their practical application was still in the development stage. In addition, Baxter and colleagues (2012) explored the potential barriers and facilitators associated with high-technology communication aids with the aim of better understanding the factors that underpin their use rather than effectiveness, from the point of view of users and of providers of these aids. They found that implementation of high-technology communication aid interventions was affected by a number of factors that included the device's ease of use; reliability; availability of technical support; voice/language of the device; decision-making process; time taken to generate a message; family perceptions and support; communication partner responses; service provision; knowledge and skills of clinicians, and resulted in limited use and abandonment of AAC devices (Waller, 2019).

One way to improve the situation with AAC devices is to enhance their performance and the degree of acceptability to users, i.e., individuals with aphasia and communication needs as well as their partners. However, in order to develop high performance communication aids, new technologies such as artificial intelligence (AI) were needed. Indeed, AI, a product of machine learning algorithms applied to large quantities of data, has become more prevalent in our daily lives and is integrated in diverse settings within the health sector, including in rehabilitation. It is precisely in this latter context that the current scoping review addresses the use of AI in aphasia rehabilitation. Recently, it has been suggested by Koch Fager and colleagues (2019) and Light and colleagues (2019) that, as AI continues to improve, it may benefit the field of AAC by reducing the cognitive load placed on those who use AAC by adapting the system to the person's needs and assisting, for example, with message correction by identifying an individual's intrinsic needs and skills, as well as extrinsic variables in the environment. Furthermore, based on the innovative uses of AI in rehabilitation in general, Light and colleagues propose several potential ways in which AI could improve AAC devices including the addition of context-aware technologies to assess ambient noise and propose adjustments to speech output volume or determine location and propose relevant vocabulary. Additionally, Sennot and colleagues (2019) point out that that there is urgency for the AAC field to consider the powerful computing tools offered by AI since these can potentially accelerate the progress in serving individuals with aphasia and other communication limitations.

Before delving into the current scoping review investigating how AI has been used in aphasia rehabilitation, we present a brief overview of some core AI concepts appearing in the articles reviewed below. For an overview of AI and an exploration of capabilities, challenges, and hazards associated with incorporating and developing AI for AAC systems, please see Sennott and colleagues (2019).

Artificial intelligence (AI), a computer science and mathematics discipline, is based on algorithms to train a machine learning model using predefined data. The basic objective of AI is to enable computers to perform tasks that typically require human intelligence, including decision making, problem solving, perception, understanding human language and translating among them. AI can be divided into two dominant approaches based on the type of data inputted: supervised and unsupervised learning. Supervised learning is done using a ground truth with prior knowledge of what the output values should be. On the other hand, unsupervised learning does not have any labelled outputs; its goal is to infer the natural structure present within a set of data points.

Machine learning, a subfield of AI, can be divided into three main methods from oldest to newest: rule-based models, probabilistic models, and neural networks which encompass deep learning. Rule-based machine learning (RBML) generates pre-defined outputs on the basis of many hardcoded rules programmed by humans in the form of if-else statements.

Probabilistic models provide a probability distribution over a fixed number of classes. There are several probabilistic classification techniques, including generative learning and discriminant learning algorithms. Naive Bayes and linear/quadratic discriminant analysis are generative learning algorithms. Linear Discriminant Analysis (LDA) is the most widely used method for in supervised analysis. It is often the starting point for more complex algorithms. The aim of the method is to maximize the ratio of the between-group variance and the within-group variance.

More recently, neural networks have been used to train machine learning thanks to the increase in computing power of the 2000s. Artificial neural networks are simply systems inspired by the functioning of biological neurons. The first neural network, the perceptron, a simple supervised neural network made up of several inputs and a single output, was created in 1957 by Frank Rosenblatt. In order to be able to work on large and complex data sets, multilayer perceptron (i.e. made up of several inputs and outputs), were introduced to processes information in only one direction: from the input nodes, through the hidden nodes to the output nodes. Neural networks differ according to the input and output size and the number of layers. Increasing the layers and allowing backward propagation, from the output to the input layer, goes beyond machine learning to enter the era of deep learning, with learning systems that can process data in depth.

1.2 Objective

The objective of this scoping review was to describe and understand how AI is currently being used in the rehabilitation of PWA. In addition, given the current belief that AI could greatly benefit the field of AAC, our secondary goal was to determine if and how AI is being integrated into AAC devices or applications for aphasia rehabilitation.

2. Methodology

2.1 Protocol

Using the Arksey and O'Malley (2005) and Levac and colleagues (2010) frameworks, we outline the specific steps for this scoping review below:

Step 1: Identifying the research question

In consultation with a medical librarian and two speech-language pathologists with extensive experience with the use of communication devices and applications with people with aphasia, we established the following research question, which guided the review: 'In what way is artificial intelligence (AI) used in language rehabilitation for people with aphasia (PWA)?' We kept this question relatively broad in order to capture not just the ways, if any, in which AI is used in high-technology augmentative and alternative communication devices or applications but also the ways in which AI in used in aphasia rehabilitation more generally.

Step 2: Identifying relevant studies

We worked with a medical librarian who provided advice regarding the selection of search terms and relevant databases that would allow us to identify relevant studies using a search strategy that was designed to be as comprehensive as possible with the available resources. To determine the relevant published literature, we performed a search of the following databases in August 2019 (in order): Medline; Embase; PsycInfo; CINAHL; Google Scholar; Cochrane Database of Systematic Reviews. Search terms used related firstly to population/condition (e.g., adult, stroke, traumatic brain injury, TBI, primary progressive aphasia, ppa). Secondly language impairment terms (e.g. aphasia, language impairment, communication impairment, word finding difficulties), together with AAC terms (e.g. high technology assistive devices, high technology communication device, AAC, AAC applications, AAC software, AAC solutions); and finally terms related to artificial intelligence (i.e. AI, artificial intelligence, smart, word prediction, voice recognition, machine learning). We used appropriate truncation symbols and wild cards in order to account for any variations in search terms. Given that the use of AI in the field of rehabilitation is a relatively recent, we limited the search to begin in the year 1990 until the present. The first author completed all searches. All identified studies were uploaded to an EndNote library where duplicates were removed (n = 118). In addition to these searches of electronic databases, we also examined the reference list of key articles and conference proceedings for any additional citations that could be relevant, and these were also added to the list of articles to review.

Step 3: Study selection

We used an iterative team approach for selecting articles and extracting data. We exported the citations (titles and abstracts) for all the eligible articles (n=663) to the Rayyan web application (Ouzzani et al., 2016) for the process of screening and selection. Each abstract was reviewed and screened by groups of two evaluators (at least one from the research team (N.A., E.K., G.J.) and 2 research assistants, A.G. and R.K., who worked on this step only) independently. If there was a question as to whether a particular article did use AI, a specialist in the field of machine learning (C.A.) was consulted. Reviewers met at the end of the evaluation process to discuss cases where there was a disagreement. When this occurred, a third reviewer was consulted to determine inclusion. The screening of studies to include was made based on the following criteria that had been developed a priori and were then revised after assessing 20 abstracts. We were willing to include the following types of articles: primary research studies, systematic reviews, meta-analyses, case studies, and conference proceedings. Articles were included only if they were published since 1990 in English or French, focused on an adult population (18 years and over) with aphasia due to stroke, head injury or a type of primary progressive aphasia (semantic dementia, non-fluent PPA etc.), and contributed to the understanding of how AI is used in the language rehabilitation for PWA. This led to choosing 27 articles or conference proceedings. When searching the reference lists of these articles, we identified an additional nine (9) articles that were included in this step of the review. After we had accessed these 36 articles and conference proceedings for eligibility and finished the charting of the data, we became aware of another recent publication that met our eligibility criteria. We evaluated this new article according to the above criteria and elected to also include it in the review. Furthermore, we identified four (4) additional articles and three (3) conference papers from the new article's reference list that were also evaluated and added to the review. In the end, we included 24 articles and four (4) conference papers that met the eligibility criteria to be included in the next step of the review for a total of 28 studies. Results from each of the steps described above, with reasons for exclusion, are presented in the PRISMA flow chart (Figure 1).

Step 4: Charting the data

To evaluate the 28 retained articles and conference papers, a full text level review for each was carried out by two independent members of the research team (N.A., E.K., or G.J.) and, conflicts were resolved by a third researcher. For each article or conference paper, data were extracted and entered into a data-charting table created for this review using Excel. This preliminary table was piloted with four articles by the evaluators after which

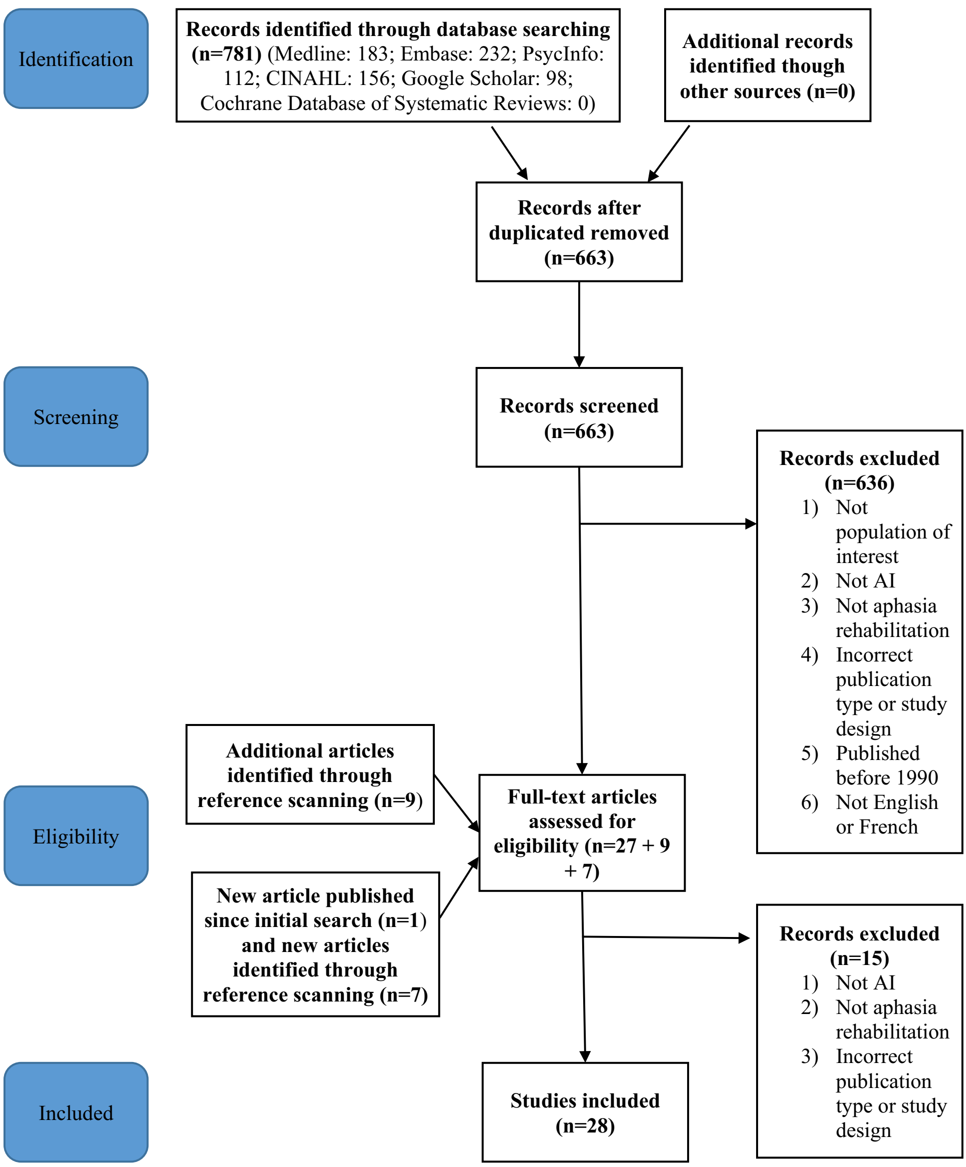

Figure 1. PRISMA flow chart.

minor adjustments were made to the table. The three evaluators met after extracting and charting the data for three articles. During these meetings, they worked by consensus, compared their extractions and resolved any potential conflicts before moving on to the next three articles. This process continued until all articles were reviewed. These meetings ensured that the table would include all the relevant information necessary to generate the themes as per step 5 described below. Where available, the data extracted and charted included the following:

- General study information including authors, title, study location, study design, study aim, participant information (age, sex, type of aphasia, cause of aphasia)
- What need or question did the researchers have to make them want (or need) to use AI or machine learning?
- What type of AI or machine learning algorithm was used?
- For what purpose was AI or machine learning algorithm used?
- How were data collected?
- Databases/norms used (either for input data and/or for testing)
- Input data
- Output data
- Did the AI or machine learning algorithm work as desired?

Stage 5: Collating, summarizing and reporting the data

The data charting tables used by each reviewer were collated into a master table. Before proceeding to the data analysis, the contents of the master table were validated during a consultation session among the three researchers who performed the charting process (N.A., E.K., and G.J.). Furthermore, the sections of the master table pertaining to AI and machine learning were validated by a fourth researcher whose expertise is in the domain of language modelling and AI (C.B.). Following validation, two members of the research team (N.A. and E.K.) independently reviewed the master table and identified a number of preliminary emerging themes that reflected how AI is used for in aphasia rehabilitation. The rest of members of the research team were then consulted to discuss the themes and ensure agreement. This process resulted in the generation of four (4) themes that address the main objective of the current review: 1) Using AI for the classification or diagnosis of aphasia/aphasic syndromes or for the classification or diagnosis of primary progressive aphasia (PPA)/PPA variants; 2) Using AI for aphasia therapy; 3) Using AI to create models of lexicalization; 4) Using AI to classify paraphasic errors. Unfortunately, as no articles addressing our secondary objective regarding the current use of AI in AAC devices for the rehabilitation of aphasia were identified, no such theme could be generated.

3. Results

The goal of the present scoping review was to synthesize the existing literature on the use of AI in the language rehabilitation of PWA; therefore, no critical review of the identified articles is presented.

The results reported here are from the 28 studies included in this scoping review (Abad et al., 2013; Akbarzadeh-T. & Moshtagh-Khorasani, 2007; Axer et al., 2000a; Axer et al., 2000b; Barbera et al., 2021; Behrns et al., 2009; Castellano et al., 2003; Fergadiotis et al., 2016; Fraser et al., 2014; Fu & Ho, 2010; Garrard et al., 2014; Järvelin & Juhola, 2011; Järvelin et al., 2004; Järvelin et al., 2006; Kiliç et al.; 2007; Konstantinopoulou et al., 2019; Le et al.,2014; Le et al.,2017; Le et al.,2018; Moshtagh-Khorasani et al., 2009; Peintner, et al.,2014; Qin et al., 2020a; Qin et al., 2020b; Sabahi, 2016; Tatari et al., 2014; Tsakonas et al., 2001; Tsakonas et al., 2004; Wade et al., 2001). We categorized the articles according to the themes mentioned above and they are presented in order of year of publication with a brief description, in Table 1.

All the articles reviewed presented either 1) data that was collected from or 2) systems/models that were tested by people with aphasia who had a variety of language backgrounds (Cantonese; Chinese (Taiwan), English, Finnish, German, Italian, Portuguese (Brazil), and Swedish) and who had a variety of different aphasia syndromes (Broca, Wernicke, Global, Anomic, Transcortical, Conduction, or Residual aphasia) and severity levels. It is of interest to note that our search did also find articles that investigated the use of an iPad™ as a tool in aphasia rehabilitation (for example, Ballard et al., 2019; Hoover & Carney, 2014; Stark & Warburton, 2018). However, these were not included because, while the iPad™ does use AI (and automatic speech recognition (ASR) technology), the main focus of these studies was not to study how the AI used in the device was affecting the rehabilitation process but rather the authors sought to determine whether and/or how the addition of an iPad™ to aphasia therapy could be beneficial.

3.1 Articles Using AI for the Classification or Diagnosis of Aphasia/Aphasic Syndromes or for the Classification or Diagnosis of Primary Progressive Aphasia (PPA)/PPA variants

Given that one of the most successful uses of AI in the medical field has been in the domain of diagnosis and classification of diseases (Shen et al., 2019), it is not surprising that the majority of articles we evaluated (n=17) used AI for the classification of aphasic syndromes or more generally for the differential diagnosis of aphasia versus no aphasia or dementia. When performed by a speech language pathologist, this comprehensive process of discriminating between healthy individuals and PWA, determining the type of aphasia syndrome, and evaluating the patients' impairment severity levels can be time-consuming. Thus, numerous attempts to automate this process with the help of AI have been made. Many of the studies sought to use AI to classify aphasia into syndromes based on language test performance. Most attempted to classify aphasia into Broca, Wernicke, global, or anomic aphasia categories (Akbarzadeh-T. & Moshtagh-Khorasani, 2007; Axer et al., 2000a; Axer et al., 2000b; Castellano et al., 2003; Järvelin & Juhola, 2011; Kiliç et al., 2007; Moshtagh-Khorasani et al., 2009; Sabahi, 2016; Tatari et al., 2014). However, Tsakonas and colleagues (2001 and 2004) used a slightly different set of aphasia syndromes: Broca, Wernicke, global, anomic, transcortical, conduction, or residual aphasia. Konstantinopoulou and colleagues (2019) also had another set of aphasia syndromes to classify aphasia: Broca, Wernicke, anomic, or conduction syndromes. Finally, Qin and colleagues used a fully automated speech assessment system for Cantonese that used automatic speech recognition (and not transcribed text) to classify aphasic speech from non-aphasic speech.

For the three (3) studies that attempted to diagnose aphasia or a language-related dementia, Järvelin and Juhola, (2011) sought to distinguish between healthy individuals

Table 1. Brief description of the 28 included studies.

Authors	Publication Type	Publication Year	Title	Aim(s) of Study	Overview of Type of AI Used	Who was System Tested On?	Input/Training Data	Output Produced	Did the AI or Algorithm Work as Desired?
Theme 1. Classification or Diagnosis (n=17)									
1a. Classification or Diagnosis of Aphasia/Aphasic Syndromes									
Axer, H., Jantzen, J., & von Keyserlingk, D. G.	Research article	2000	An aphasia database on the internet: a model for computer-assisted analysis in aphasiology	To develop a tool for teaching medical students, postgraduates, and engineering students about data modeling and its medical applications.	Two artificial neural networks (multilayer perceptrons: artificial neuronal networks).	Dataset of 254 aphasic patients on the Aachen Aphasia Test (AAT) (Axer et al., 2000c)	Data of 254 aphasic patients (contains the diagnosis of the aphasia type, profiles of an aphasia test battery (AAT), Computed Tomography (CT) information for 147 patients.)	Classification/ Diagnosis of aphasic syndromes: Broca, Wernicke, Global, and Anomic	Mixed. "The first model produced correct diagnoses in 87% of the test cases, and the second model produced correct diagnoses in 92% of the test cases. The accuracy of the two classifiers differed in respect to the aphasia type "
Axer, H., Jantzen, J., Berks, G., & Keyserlingk, D. G. V.	Research article	2000	Aphasia classification using neural networks	To develop an educational tool accessible from the TEDServer in order to perform interdisciplinary teaching of soft computing applications in medicine.	Two multilayer perceptrons were used to classify the type of aphasia.	Dataset of 164 aphasic patients on the Aachen Aphasia Test (AAT) (Axer et al., 2000c)	Data of 164 aphasic patient (diagnosis of the aphasia type, data from spontaneous speech subtests of the AAT)	Classification/ Diagnosis of aphasic syndromes: Broca, Wernicke, Global, and Anomic	Mixed. "The 1st classifier diagnosed anomic aphasia 75% correctly and Wernicke aphasia 83% correctly, while Broca and global aphasia was diagnosed considerably better (95% and 97% respectively). In contrast, the 2nd classifier diagnosed 83% of the anomic cases and 95% of the Wernicke aphasics correctly."

(Continued)

Table 1. (Continued).

Authors	Publication Type	Publication Year	Title	Aim(s) of Study	Overview of Type of AI Used	Who was System Tested On?	Input/Training Data	Output Produced	Did the AI or Algorithm Work as Desired?
Tsakonas, A., Dounias, G. D., Graf von Keyserlingk, D., & Axer, H.	Research article	2001	Hybrid computational intelligence for handling diagnosis of aphasia	To present two models based on hybrid computational intelligence, for the classification between different types of aphasia.	Hybrid scheme consisting of a genetic programming core and a supporting heuristic rule-based classification system.	Dataset of 254 aphasic patients on the Aachen Aphasia Test (AAT) (Axer et al., 2000c)	Data from an unknown number of aphasic patients on the AAT	Classification/ Diagnosis of aphasic syndromes: Broca, Wernicke, Global, and Anomic Transcortical, Conduction, and Residual	Mixed. "The first model was implemented only for the four major types of aphasia. This approach enabled the authors to draw conclusions on the model's effectiveness as compared to previous intelligent techniques found in literature. The results were comprehensive for medical experts and they are characterized as close to previous approaches. They have also enabled the experts to draw conclusions or to reconfirm known medical results in some cases. The second alternative classification model was applied to the full range of Aphasia's subtypes, in order to perform as an assisting decision tool. These latter results were not very comprehensible.

(Continued)

Table 1. (Continued).

Authors	Publication Type	Publication Year	Title	Aim(s) of Study	Overview of Type of AI Used	Who was System Tested On?	Input/Training Data	Output Produced	Did the AI or Algorithm Work as Desired?
Castellano, C., Fanelli, A.M., & Mencar, C.	Conference paper	2003	Discovering human understandable fuzzy diagnostic rules from medical data	To model a diagnostic problem by means of a set of fuzzy rules that have both the features of transparency and predictive accuracy.	Crisp Double Clustering (CDC) algorithm.	Dataset of 146 aphasic patients on the Aachen Aphasia Test (AAT) (Axer et al., 2000c)	Data of 146 aphasic patients (contains the diagnosis of the aphasia type, profiles of an aphasia test battery (AAT), Computed Tomography (CT) information for 147 patients.)	Classification/ Diagnosis of aphasic syndromes: Broca, Wernicke, Global, and Anomic	Yes. " … many fuzzy inference systems based on different number diagnostic rules and sets per symptom have been derived, producing a mean prediction accuracy of about 86% for 'spontaneous speech` and 91% for `comprehensive model`".
Tsakonas, A., Dounias, G., Jantzen, J., Axer, H., Bjerregaardd, B., & Graf von Keyserlingk, D.	Research article	2004	Evolving rule-based systems in two medical domains using genetic programming	To demonstrate and compare the application of different genetic programming (GP) based intelligent methodologies for the construction of rule-based systems in two medical domains: the diagnosis of aphasia's subtypes and the classification of pap-smear examinations.	Machine learning, Standard genetic programming; Genetic programming for the production of crisp rule-based systems (CRBS-GP); and Genetic programming for the production of fuzzy rule-based systems (FRBS-GP).	Dataset of 145 aphasic patients on the Aachen Aphasia Test (AAT) (Axer et al., 2000c)	Data from 145 aphasic patients (diagnosis of the aphasia type, data from six sub-tests of spontaneous speech from the AAT)	Classification/ Diagnosis of aphasic syndromes: Broca, Wernicke, Global, Anomic, Transcortical, Conduction, and Residual	Mixed. "The accuracy of classification on test data of the acquired GP crisp and fuzzy rule bases is lower than the accuracy achieved by neural networks and higher than the accuracy obtained by machine learning. These GP crisp and fuzzy rule bases however, retain higher comprehensibility, as compared with the competitive methodologies … "
Kiliç, K., Uncu, O., & Türksen, I.B.	Research article	2007	Comparison of different strategies of utilizing fuzzy clustering in structure identification	To analyze three possible approaches of incorporating fuzzy clustering in the structure identification phase of fuzzy modelling and we compare the performances of these algorithms in a medical diagnosis classification problem (aphasia diagnosis).	Three different approaches in which one can utilize fuzzy clustering: the first one is based on input space clustering (M-A), the second one considers clustering realized in the output space (Castellano), the third one is concerned with clustering realized in the combined input-output space (U&T).	Dataset of 146 aphasic patients on the Aachen Aphasia Test (AAT) (Axer et al., 2000c)	Data from 146 aphasic patients (4 attributes and the diagnoses for AAT)	Classification/ Diagnosis of aphasic syndromes: Broca, Wernicke, Global, and Anomic	Mixed . "The classi … cation performances of the three algorithms in terms of percentage of successful classi … cations: M-A: 89.8%; Castellano et al: 78.4%; U&T: 83.6%."

(*Continued*)

Table 1. (Continued).

Authors	Publication Type	Publication Year	Title	Aim(s) of Study	Overview of Type of AI Used	Who was System Tested On?	Input/Training Data	Output Produced	Did the AI or Algorithm Work as Desired?
Akbarzadeh-T., R., & Moshtagh-Khorasani, M.	Research article	2007	A hierarchical fuzzy rule-based approach to aphasia diagnosis	To evaluate a hierarchical fuzzy rule-based structure that considers the effect of different features of aphasia by statistical analysis in its construction.	A hierarchical fuzzy rule-based structure is proposed that is composed of two layers.	Dataset of 146 aphasic patients on the Aachen Aphasia Test (AAT) (Axer et al., 2000c)	Data from 146 aphasic patients have been split in two halves: first half as training set and the second half as testing set. (Input: two sets of data from the AAT (data from spontaneous speech interview and comprehensive model data))	Classification/ Diagnosis of aphasic syndromes: Broca, Wernicke, Global, and Anomic	Yes. "Statistical analysis reveals that the proposed fuzzy approach has a better performance for accuracy while also using fewer features as compared with artificial neural networks. . . . the proposed fuzzy approach clearly provides better diagnosis when data are limited as in spontaneous speech."
Moshtagh-Khorasani, M., Akbarzadeh-T, M. R., Jahangiri, N., & Khoobdel, M.	Research article	2009	An intelligent system based on fuzzy probabilities for medical diagnosis- a study in aphasia diagnosis	To proposed the use of fuzzy probabilities for better medical classification and implemented it on Aphasia diagnosis.	Fuzzy probability	Dataset of 164 aphasic patients on the Aachen Aphasia Test (AAT) (Axer et al., 2000c)	Data from 164 aphasic patients (Two sets of data from the AAT (data from spontaneous speech interview and comprehensive model data))	Classification/ Diagnosis of aphasic syndromes: Broca, Wernicke, Global, and Anomic	Yes. "The best result for first classifier is 91.30% and for second classifier is 95.55% correct diagnosis, as mean of correct diagnoses for the four classes. Fuzzy probability estimator approach is about five times quicker than neural networks and about 1.7 times quicker than our previous work, the hierarchical fuzzy rule based method Akbarzadeh-T & Moshtagh-Khorasani, 2007)"

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Table 1. (Continued).

Authors	Publication Type	Publication Year	Title	Aim(s) of Study	Overview of Type of AI Used	Who was System Tested On?	Input/Training Data	Output Produced	Did the AI or Algorithm Work as Desired?
Järvelin, A. & Juhola, M.	Research article	2011	Comparison of machine learning methods for classifying aphasic and non-aphasic speakers	To investigate the suitability of machine learning classifiers to separate between healthy individuals from aphasic patients and to classify aphasic patients to the groups based on their performance in the aphasia tests.	Eight machine learning classifiers (Multi-Layer Perceptrons (MLPs), Probabilistic Neural Networks (PNNs), Self-Organizing Maps (SOMs), k-nearest neighbor (k-NN) classifier, k-means classifier (k-means), decision tree classifier (tree), discriminant analysis and Bayesian classifier).	1- Dataset of 23 aphasic patients and averaged naming distribution of 60 healthy control subjects; 2- Dataset of naming distributions of 12 Alzheimer disease patients and 10 vascular disease patients; 3- Dataset of 265 aphasia patients on the Aachen Aphasia Test (AAT) (Axer et al., 2000c)	1- Aphasic data: Aphasia dataset of Dell et al. (Philadelphia Naming Test (PNT)); 2-Dementia data: Dementia dataset of Järvelin et al. (Finnish version of the Boston Naming Test (BNT)); 3- Aphasic data: PatLight aphasia dataset of Axer et al. (Aachen Aphasia Test (AAT))	Classification/ Diagnosis: 3 types (1-Diagnosis of aphasia versus healthy controls; 2- Classification of Alzheimer patients versus vascular disease patients; 3- Classification of aphasic syndromes: Broca, Wernicke, Global, and Anomic)	Mixed. "With the first (Dell et al.) and the third data set (PatLight), the classifiers could successfully be used for the classification task, while the results with the second data set were less encouraging."
Tatari, T., Akbarzadeh-T, M.-R., & Mazouchi, M.	Research article	2014	A self-organized multi agent decision making system based on fuzzy probabilities: The case of aphasia diagnosis	To introduce a self-organized multi-agent system (SOMAS) that decides based on fuzzy probabilities. To demonstrate the applicability of this method on the problem of aphasia diagnosis.	Self organized multi agent system (SOMAS) which decides about aphasia diagnosis based on fuzzy probabilities.	Dataset of 146 aphasic patients on the Aachen Aphasia Test (AAT) (Axer et al., 2000c)	Data 146 aphasic patients (30 different tests (features) on the Aachen Aphasia Test (AAT))	Classification/ Diagnosis of aphasic syndromes: Broca, Wernicke, Global, and Anomic	Yes. "Best result 94.49%. The proposed SOMAS with fuzzy probability outplays other previous methods employed for Aphasia diagnosis in the case of mean performance percent- age and best performance, also its superior performance is reported in robustness of diagnosis."
Sabahi, F.	Research article	2016	A novel generalized belief structure comprising unprecisiated uncertainty applied to aphasia diagnosis	To present a new generalization of the Dempster–Shafer Theory (DST).	Validity-modified fuzzy-valued measure Belief structure.	Dataset of 146 aphasic patients on the Aachen Aphasia Test (AAT) (Axer et al., 2000c)	We divide the sub-databases of aphasia type into three random sets: training set, validation set, and testing set. Inputs of each rule are Aachen Aphasia Test (AAT) scores	Classification/ Diagnosis of aphasic syndromes: Broca, Wernicke, Global, and Anomic	Yes. "The best result in our approach is 98.90%. . . . the mean percentage of success for the proposed approach is 94.64% which is greater than other approaches' success rates . . . "

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Table 1. (Continued).

Authors	Publication Type	Publication Year	Title	Aim(s) of Study	Overview of Type of AI Used	Who was System Tested On?	Input/Training Data	Output Produced	Did the AI or Algorithm Work as Desired?
Konstantinopoulou, G., Kovas, K., Hatzilygeroudis, I., & Prentzas, J.	Research article	2019	An approach using certainty factor rules for aphasia diagnosis	To present a rule-based approach used for aphasia diagnosis.	The multilayer feedforward neural network (ACRES (Automatic CReator of Expert Systems)).	Dataset of 164 records from AphasiaBank (MacWhinney et al., 2011)	Each record in the dataset consisted of nineteen attributes, that is, eighteen input attributes and one output attribute from AphasiaBank.	Classification/ Diagnosis of aphasic syndromes: Broca's, Wernicke's, Anomic and Conduction	Mixed. "Experimental results show that the specific rule-based approach performs well compared to a decision tree method and feedforward neural networks. More specifically, the rule-based approach performs slightly worse than the other methods in terms of classification accuracy but uses less features to produce an output."
Qin, Y., Lee, T. & Kong, A.P.H.	Research article	2020	Automatic assessment of speech impairment in Cantonese-speaking people with aphasia	To develop a fully automated speech assessment system for Cantonese-speaking PWA. The system takes in narrative speech produced by the subject being assessed and makes prediction on the severity of aphasia based on the characteristics of input speech.	A deep neural network (DNN) based automatic speech recognition (ASR) system is developed for aphasic speech by multi-task training with both in-domain and out-of-domain speech data. Story-level embedding and siamese network are applied to derive robust text features, which can be used to quantify the difference between aphasic speech and unimpaired one.	Dataset of audio recordings of narrative speech from 105 aphasic patients and 149 unimpaired subjects from Cantonese AphasiaBank (Kong & Law, 2019)	For acoustic model, training are divided into two parts: in-domain data (12.6 hours of recordings from 101 unimpaired speakers and 1.8 hours of speech from 17 unimpaired subjects are used for ASR performance evaluation. and out-of-domain data (from two publicly available Cantonese speech databases: (King-ASR -086 & CUSENT)	Classification/ Diagnosis of aphasic versus non-aphasic speech	Yes. "It has been demonstrated that the proposed data-driven text features are very effective in detecting language impairment in aphasic speech."

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Table 1. (Continued).

Authors	Publication Type	Publication Year	Title	Aim(s) of Study	Overview of Type of AI Used	Who was System Tested On?	Input/Training Data	Output Produced	Did the AI or Algorithm Work as Desired?
Qin, Y., Wu, H., Lee, T. & Kong, A.P.H.	Research article	2020	An End-to-End Approach to Automatic Speech Assessment for Cantonese-speaking People with Aphasia	To report preliminary results on Cantonese-speaking people with aphasia's speech assessment using the end-to-end approach. The assessment is formulated as a binary classification task to discriminate PWA with high scores of subjective assessment from those with low scores.	2-layer Gated Recurrent Unit (GRU) and Convolutional Neural Network (CNN) models are applied to realize the end-to-end mapping from basic speech features to the classification outcome.	Dataset of audio recordings of narrative speech from 105 aphasic patients and 149 unimpaired subjects from Cantonese AphasiaBank (Kong & Law, 2019)	91 PWA, the binary classification experiment is carried out with the arrangement of 5-fold cross validation. In each fold, 80% of the subjects are used for training and the rest 20% subjects are used for test. 10% of subjects are randomly selected from training subjects as the validation data.	Classification of aphasia severity, PWA with High-Aphasia Quotient (AQ ≥ 90) versus those with Low-AQ (AQ < 90).	Mixed. "Experimental results show that the end-to-end approach can achieve comparable performance to the conventional two-step approach in the classification task, and the CNN model is able to learn impairment-related features that are similar to the hand-crafted features. The experimental results also indicate that CNN model performs better than 2-layer GRU model in this specific task."
1b. Classification or Diagnosis of Primary Progressive Aphasia (PPA)/PPA Variants									
Fraser, K. C., Meltzer, J. A., Graham, N. L., Leonard, C., Hirst, G., Black, S. E., & Rochon, E.	Research article	2014	Automated classification of primary progressive aphasia subtypes from narrative speech transcripts	1- To develop a machine learning classifier that would analyze speech samples and be able to distinguish between control participants and participants with progressive nonfluent aphasia (PNFA) or semantic dementia (SD), as well as between the two patient groups. 2- To identify the automatically extracted features that best distinguish the groups, and to compare this with results in the literature that are based on traditional (manual) analysis methods.	Three machine learning classifiers from the WEKA machine learning toolkit (Naive Bayes; logistic regression; Support Vector Machines).	10 patients with semantic dementia (SD); 14 patients with progressive nonfluent aphasia (PNFA); 16 age and education-matched healthy controls	Transcriptions of speech samples elicited from the Cinderella Story	Classification/ Diagnosis (SD, control or PNFA)	Yes. " . . . we have demonstrated that fairly high classification accuracies can be achieved through automated quantitative analysis of speech samples with relatively little human interaction."

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Table 1. (Continued).

Authors	Publication Type	Publication Year	Title	Aim(s) of Study	Overview of Type of AI Used	Who was System Tested On?	Input/Training Data	Output Produced	Did the AI or Algorithm Work as Desired?
Garrard, P., Rentoumi, V., Gesierich, B., Miller, B., & Gorno-Tempini, M. L.	Research article	2014	Machine learning approaches to diagnosis and laterality effects in semantic dementia discourse	To explore the potential of automatic text classification to classify transcribed speech samples along clinical dimensions, using vocabulary data alone.	Two related machine learning algorithms (Naive Bayes Gaussian (NBG) and naive Bayes multinomial (NBM)).	32 patients with semantic dementia (SD) and 10 age matched, cognitively normal controls (NC). Within the SD group: 21 showed a L > R pattern of temporal lobe asymmetry, and 11 with the R > L pattern.	Transcriptions of speech samples elicited from picnic picture description test and structural MR imaging	Classification/ Diagnosis: (SD versus NC; L > R versus R > L distinctions (of SD)	Yes. " . . . using two variants (Gaussian (NBG) and multivariate (NBM)) of the naive Bayes approach, we found classifiers that could distinguish between SD patients and controls and between L > R and R > L SD patients with a high degree of accuracy."
Peintner, B., Jarrold, W., Vergyri, D., Richey, C., Tempini, M. L. G., & Ogar, J.	Conference paper	2014	Learning diagnostic models using speech and language measures	To describe results that show the effectiveness of machine learning in the automatic diagnosis of certain neurodegenerative diseases, several of which alter speech and language production.	Extracted features of the audio signal and the words the patient used, which were obtained using our automatic speech recognition (ASR) algorithms, our phoneme duration measurement tools, and existing linguistic content analysis (LCA) tools. Using off-the-shelf machine learning algorithms (SimpleLogistic (logistic regression), J48 (decision tree), and MultiLayeredPerceptron (neural network)., we learned models that predict the diagnosis of the patient using subsets of the extracted features.	9 healthy control subjects and 30 patients diagnosed with one of 3 clinical variants of Frontotemporal Lobar Degeneration (FTLD)	3-5 minutes of speech recorded while the patient performed Part I of the Western Aphasia Battery [5]. This task elicits spontaneous speech as part of a standardized speech and language assessment protocol. (Data obtained from the UCSF Memory and Aging Center database.)	Classification/ Diagnosis: (Healthy controls versus each specific FTLD subtype: (behavioral variant of Frontotemporal dementia (bvFTD), semantic dementia (SD) and progressive nonfluent aphasia (PNFA)).	Yes. "We have shown that simple measures of speech and language can be used to predict the diagnosis of a patient with significant accuracy. If we can continue to improve results, e.g., by adapting ASR to produce lower WER, or by testing our system on larger samples, we will be closer to a deployable, in-home speech analysis system, which can provide significant value to clinicians and their patients in the near future."

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Authors	Publication Type	Publication Year	Title	Aim(s) of Study	Overview of Type of AI Used	Who was System Tested On?	Input/Training Data	Output Produced	Did the AI or Algorithm Work as Desired?
Theme 2. Aphasia Therapy (n=7)									
2a Aphasia Therapy – Feedback on vocal output for at-home language exercise									
Le, D., Licata, K., Mercado, E., Persad, C., & Provost, E. M.	Conference paper	2014	Automatic analysis of speech quality for aphasia treatment	To develop an intelligent system capable of providing automatic feedback to patients about their verbal output during practice, by testing automatic classifiers that allow the system to be able to estimate the quality of speech produced by patients, thus improving the effectiveness of in-home exercises to support traditional therapy as needed.	Several commonly-used classifiers, including C4.5 Decision Tree, Logistic Regression, Naive Bayes, Random Forest, and Support Vector Machine.	6 patients (5 male, 1 female, age ranged rom 49-70 years) with aphasia	A natural speech corpus containing over two hours of aphasic speech collected from the patients with aphasia.	Classification of aphasic speech using 4 criteria/ aspects: Prosody Clarity, Fluidity, and Effort	Yes. "Our results indicate that it is possible to construct an automatic classifier comparable to the average human for estimating each of the four aspects (Prosody, Clarity, Fluidity, and Effort) of speech quality."

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Table 1. (Continued).

Authors	Publication Type	Publication Year	Title	Aim(s) of Study	Overview of Type of AI Used	Who was System Tested On?	Input/Training Data	Output Produced	Did the AI or Algorithm Work as Desired?
2b. Aphasia Therapy – Use of Automatic Voice/Speech Recognition Systems (ASR)									
Wade, B. Petheram, R., & Cain, J.	Research article	2001	Voice recognition and aphasia: Can computers understand aphasic speech?	To investigate the accuracy of VRS (Voice recognition software) with aphasic speech, with the specific aim of evaluating its feasibility as an input device for aphasia therapy software.	The software used was Dragon Naturally Speaking Preferred version 4.01.	6 patients with aphasia following stroke (5 male and 1 female, age ranged from 43-68 years) and 5 nonimpaired subjects (2 male and 3 female, age ranged from 30-64 years)	Items for single word level production were items 1- 50 from PALPA 57. The short phrases used for the phrase level condition included a total of 100 words. Half of the stimulus items in each condition were randomly assigned to a training group. The remainder received no training and acted as a control group to measure the software's ability to generalize `learning' from trained to untrained items.	Recognition of aphasic speech and speech transcription	Mixed. "For single word level condition: Of the 5 control subjects, the software reached criteria level accuracy (95% accuracy or higher over at least 2 sessions) for C1, C2 and C4 within the five sessions, but failed to do so for C3 and C5. Of the six subjects with aphasia, software accuracy for S5 alone reached criteria and maintained it, although for all subjects 95% accuracy was reached in at least one session during training. For the phrase level condition: Three of the controls (C2, C4 and C5) met criteria for accuracy within the five sessions. Of the aphasic subjects, only S1, S2 and S5 met these criteria in the phrase level condition, but accuracy levels for S2 were not maintained.

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Authors	Publication Type	Publication Year	Title	Aim(s) of Study	Overview of Type of AI Used	Who was System Tested On?	Input/Training Data	Output Produced	Did the AI or Algorithm Work as Desired?
Abad, A., Pompili, A., Costa, A., Trancoso, I., Fonseca, J., Leal, G. et al	Research article	2013	Automatic word naming recognition for an on-line aphasia treatment system	To present an on-line system designed to behave as a virtual therapist incorporating automatic speech recognition technology that permits aphasia patients to perform word naming training exercises.	AUDIMUS is a hybrid speech recognizer that follows the connectionist approach. It combines the temporal modelling capacity of Hidden Markov Models (HMMs) with the pattern discriminative classification of multilayer perceptrons (MLP).	16 patients (10 male, 6 female) with word naming difficulties but without (or very low) articulatory or speech production impairments	The version of AUDIMUS integrated in VITHEA uses an acoustic model trained with 57 hours of down sampled Broadcast News data and 58 hours of mixed fixed-telephone and mobile-telephone data in European Portuguese	Recognition and processing of aphasic speech (individually presented words) and decision regarding if the word produces is correct	Yes. " . . . we have shown that it is possible to achieve highly correlated global word naming scores and high performance word verification rates even for different types of patients and acoustic conditions."
Le, D., Licata, K., & Provost, E. M.	Research article	2018	Automatic quantitative analysis of spontaneous aphasic speech	To perform one of the first large-scale quantitative analysis of spontaneous aphasic speech based on automatic speech recognition (ASR) output. To describe our acoustic modeling method and propose a set of clinically-relevant quantitative measures that are shown to be highly robust to automatic transcription errors. Finally, to demonstrate that these measures can be used to accurately predict the revised Western Aphasia Battery (WAB-R) Aphasia Quotient (AQ) without the need for manual transcripts.	Deep multi-task BLSTM-RNN on log Mel filterbank coefficient (MFB) features augmented with utterance-level i-vectors.	Dataset of 401 patients with aphasia (238 male, 163 female) and 187 control speakers (85 male, 102 female) from AphasiaBank (MacWhinney et al., 2011)	Data from 19 sub-datasets of AphasiaBank, 130.9 h of speech. Withhold 15% of training Aphasia speakers from each sub-dataset to form a held-out development set.	Automatic analysis of aphasic speech for aphasia assessment	Yes. "Our acoustic modeling method based on deep BLSTM-RNN and utterance- level i-vectors sets a new benchmark for aphasic speech recognition on AphasiaBank. We show that with the help of feature calibration, our proposed quantitative measures are robust against ASR errors and can potentially be used to assist with clinical diagnosis and/or progress monitoring. Finally, we demonstrate the efficacy of these measures by using them to predict WAB-R AQ with promising accuracy."

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Table 1. (Continued).

Authors	Publication Type	Publication Year	Title	Aim(s) of Study	Overview of Type of AI Used	Who was System Tested On?	Input/Training Data	Output Produced	Did the AI or Algorithm Work as Desired?
Barbera, D. S., Huckvale, M., Fleming, V., Upton, E., Coley-Fisher, H., Doogan, C et al.	Research article	2021	NUVA: A Naming Utterance Verifier for Aphasia Treatment	To present and assess the feasibility and stability of NUVA, a tailor-made ASR system incorporating a deep learning element to assess word naming attempts in people with aphasia.	Keras deep learning framework with TensorFlow.	8 patients (6 male, 2 female) with chronic post-stroke anomia	To train the acoustic model: WSJCAM0 (a corpus of British healthy English speakers)	Classification of 'correct' versus' incorrect' naming attempts from aphasic stroke patients	Yes. " . . . the system's performance accuracy ranged between 83.6% to 93.6%, with a 10-fold cross-validation mean of 89.5%. This performance was not only significantly better than a baseline created for this study using one of the leading commercially available ASRs (Google speech-to-text service) but also comparable in some instances with two independent SLT ratings for the same dataset."
2b. Aphasia Therapy - Assisting Communication									
Behrns, I., Hartelius, L., & Wengelin, A.	Research article	2009	Aphasia and computerised writing aid supported treatment	To investigate whether writing difficulties in aphasia might be reduced by training supported by a computerised writing aid.	Two writing aids: a word prediction program (SaidaH (Oribi AB)) and a spell checker program (Stava Rätt 3.0H (Oribi AB)).	3 patients (with aphasia (2 Broca's; 1 mixed nonfluent)	The participants were offered books with large and expressive pictures in an area of personal interest and were asked to write about what they saw in the pictures.	Word prediction or spell-checking	Yes. " . . . for the participants in this study the computerised writing aid did partly compensate for their writing difficulties."
Fu, Y. F. & Ho, C. S.	Research article	2010	Building intelligent communication systems for handicapped aphasiacs	To develop an intelligent and easy-to-use communication system (including proper hardware and software) that makes it possible for handicapped aphasiacs to perform basic communication tasks naturally and affordably.	Radial Basis Function Neural Network-Based Classification.	No participants tested the system	Finger Language Recognition Subsystem	Text for communication	Yes. "We have demonstrated that efficient and effective manipulation of the virtual keyboard using finger-language-based interaction techniques is possible."

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Table 1. (Continued).

Authors	Publication Type	Publication Year	Title	Aim(s) of Study	Overview of Type of AI Used	Who was System Tested On?	Input/Training Data	Output Produced	Did the AI or Algorithm Work as Desired?
Theme 3. Models of Lexicalization									
Järvelin, A., Juhola, M., & Laine, M.	Research article	2004	A neural network model of lexicalization for simulating the anomic naming errors of dementia patients	To present a neural network model for simulating the anomic naming errors of Finnish-speaking AD and VaD patients.	DTS model for simulating naming errors of Finnish-speaking people. Perceptron based neural network model lexicalization model consists of three neural networks: the lexical-semantic network and two separate phoneme networks.	Data set of 12 Alzheimer's disease patients; 10 vascular dementia patients, 19 neurologically intact controls on the Finnish version of the Boston Naming Test (Laine et al., 1997)	Data of 41 people from Finnish version of the Boston Naming Test (279 Finnish nouns)	Simulation of naming errors of Finnish-speaking dementia patients	Yes. " . . . the model was able to simulate the naming distributions of different dementia patients as well as those of intact control subjects very precisely."
Järvelin, A., Juhola, M., & Laine, M.	Research article	2006	A neural network model for the simulation of word production errors of Finnish nouns.	To build a model of lexicalization to simulate the naming data of actual aphasic patients.	DTS model for simulating naming errors of Finnish-speaking people. The perceptron based neural network model lexicalization model consists of three neural networks: the lexical-semantic network and two separate phoneme networks.	Dataset of 279 nouns (Laine et al., 1998)	Data of 9 patients with aphasia (3 Anomic, 2 Broca's, 2 Conduction, and 3 Wernicke's)	Simulation of naming errors of Finnish-speaking patients with aphasia	Yes. "The model was reasonable in simulating word production errors in this heterogeneous group of aphasic patients."
Theme 4. Identification/Classification of Paraphasic Errors									

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Table 1. (Continued).

Authors	Publication Type	Publication Year	Title	Aim(s) of Study	Overview of Type of AI Used	Who was System Tested On?	Input/Training Data	Output Produced	Did the AI or Algorithm Work as Desired?
Fergadiotis, G., Gorman, K., & Bedrick, S.	Research article	2016	Algorithmic classification of five characteristic types of paraphasias	The development and evaluation of a series of algorithms developed to perform automatic classification of paraphasic errors according to an already-existing typology.	3 automated tools: 1) frequency norms from the SUBTLEXus database (Brysbaert & New, 2009) to differentiate nonword errors and real-word productions. 2) implemented a phonological-similarity algorithm to identify phonologically related real-word errors. 3) assessed the performance of a semantic-similarity criterion that was based on word2vec (Mikolov, Yih, & Zweig, 2013).	Subset of the MAPPD data set (Mirman et al., 2010): 7111 paraphasic errors of 251 participants on the Philadelphia Naming Test (PNT).	Dataset of 521 participants. All were native English speaking individuals with aphasia consequent to left-hemisphere stroke.	Classification of paraphasic errors	Yes. "Overall, the scoring algorithms described in this article replicated human scoring for the major categories of paraphasias with high accuracy".
Le, D., Licata, K., & Provost, E. M.	Conference paper	2017	Automatic Paraphasia Detection from Aphasic Speech: A Preliminary Study	To investigate the feasibility of detecting phonemic and neologistic paraphasias automatically from aphasic speech.	For automatic speech recognition (ASR): Multi-task deep bidirectional long-short term memory recurrent neural network (DBLSTM-RNN, consists of four hidden BLSTM layers, each with 1200 units (600 for forward, 600 for backward)) to predict both the correct senone and monophone labels for each frame. (The senone and monophone output layers contain 4550 and 46 units, respectively. For paraphasia classification: three standard classification algorithms: decision trees (DT), logistic regression (LR), and support vector machines (SVM).	Dataset from AphasiaBank (MacWhinney et al., 2011)	Fridriksson sub-dataset of the Scripts portion containing recordings of 12 patients with aphasia reading from four predefined scripts (advocacy, eggs, vast, and weather).	Classification of phonemic and neologistic paraphasic errors	Yes. "We demonstrated the feasibility of detecting paraphasias from known target transcripts. We showed the utility of utterance- and speaker-level analysis when target transcripts are generated automatically with ASR."

and PWA and between patients with Alzheimer's disease (AD) and vascular disease. Fraser and colleagues (2014) sought to distinguish between healthy individuals and those with progressive nonfluent aphasia (PNFA) and semantic dementia (SD), as well as between the two patient groups. Garrard and colleagues (2014) sought to differentiate healthy individuals from those with SD, as well as to differentiate between left-hemisphere dominant versus right-hemisphere dominant distinctions of SD. Finally, Peintner and colleagues (2014) sought to distinguish healthy individuals and those with frontotemporal lobar degeneration (FTLD) as well as between three specific FTLD subtypes (behavioral variant of frontotemporal dementia (bvFTD), SD, PNFA).

It is also of interest that of the above-mentioned studies, only two studies (Fraser et al., 2014 and Garrard et al., 2014) recruited people whose data they then used to train and to test their AI model(s). All others relied instead on previously collected data sets. Konstantinopoulou and colleagues (2019) used data from the English-language AphasiaBank database (MacWhinney et al., 2011) to train and test their multilayer feed forward neural network and Qin and colleagues (2020 a and b) used the Cantonese-language AphasiaBank database (Kong and Law, 2019). All of the other studies in this section used the dataset (or a subset of the dataset) of 254 PWA using the Aachen Aphasia Test (AAT) (Axer at al., 2000c) to train and test their models. This is likely because while large scale language datasets exist for aphasic populations (Axer et al., 2000c and more recently AphasiaBank), no such datasets are available for use with populations with neurodegenerative disorders.

In terms of performance accuracy, results show that regardless of the type of AI approach used (e.g. including multilayer perceptrons, artificial neuronal networks, rule-based classification system, genetic programming, probabilities, machine learning classifiers, automatic speech recognition (ASR), and machine learning algorithms), all were able to differentiate between aphasic syndromes with a relatively high level of accuracy.

3.2 Articles Using AI for Aphasia Therapy

Another subset of articles we reviewed used AI as part of or to augment an aphasia therapy intervention. Of these seven (7) studies, one (1) presented and evaluated an AI-based application that provides feedback to PWA on their verbal output when performing language exercises at home, four (4) used and evaluated automatic speech recognition (ASR) technology as part of computerized assessments or interventions for PWA, and two (2) presented and evaluated novel AI-based therapies.

Le and colleagues (2014) presented a system (a mobile application) that sought to provide automatic feedback to people with aphasia about their verbal output during practice at home in order to complement traditional therapy. The AI classification accuracy performance was deemed to be similar to that of a human. However, all aphasic speech had to be transcribed and coded by a person prior to analysis by the AI classifier, which added a substantial burden to using the system. While the automatic recognition of aphasic speech has long been a major hurdle to overcome for ASR technology, this area of research has been showing more promise in recent years. Wade and colleagues (2001) attempted to use a commercially available ASR (then called voice recognition software or VRS) software called Dragon Naturally Speaking) to recognise and transcribe aphasic speech with the aim of evaluating its feasibility as an input device for aphasia therapy software. While the software was somewhat successful for the recognition of single words, at the phrase level the software did not perform well as it was not adapted to aphasic speech.

More recently, research has focused on developing intelligent systems that can recognise aphasic speech using ASR with the ultimate goal of incorporate these into therapy. Le and colleagues (2018) created and tested an ASR system that could allow speech-language pathologist (SLPs) to analyze quantities of aphasic speech data quickly and reliably. Results showed that the system made relatively few ASR errors and could potentially be used to assist SLPs with clinical diagnosis and/or progress monitoring. However, they were careful to note that, while potentially useful to SLPs, analyses showed that individuals with severe aphasia would likely have important difficulties using applications that rely mostly on ASR output. In 2013, Abad and colleagues presented an on-line system (called VITHEA) that was designed to behave as a virtual therapist by incorporating ASR automatic word naming recognition module (called AUDIMUS) that allowed Portuguese-speaking aphasic patients with word-finding difficulties to perform word naming training exercises. The system was successful in recognising and processing aphasic speech (individually presented words) and deciding whether the words produced were correct. However, the authors conceded that it was unclear whether the accuracy achieved was sufficient for a satisfactory user experience and if it contributed to the recovery of its users. More recently, in 2021, Barbera and colleagues also presented a similar system (called NUVA) to automatically assess word naming attempts in PWA using ASR, this time in English speaking individuals. This system also successfully recognised and processed aphasic speech and correctly classified correct and incorrect naming attempts. While the authors point out that NUVA achieved both a more accurate and less variable performance when compared to VITHEA they point out that their performance data, while encouraging, are best seen as a proof of concept and that further validation with a larger sample of PWA is still required.

An additional two studies used AI in aphasia therapy interventions to attempt to help people with aphasia to communicate better (Behrns et al., 2009; Fu & Ho, 2010). These two studies focused on different language modalities to try to help or improve their communication abilities. In the first study, Behrns and colleagues (2009) used two commercially available computerised writing aids that employ AI and assessed whether writing difficulties could be reduced in three PWA with a 9-week intervention of training on one of the two aids, either a word prediction program (SaidaH (Oribi AB)) or a spell checker program (Stava Rätt 3.0H (Oribi AB)). Results showed that using the computerized writing aid could compensate, in part, for writing difficulties by facilitating the word-generating process and making the revision process more efficient for PWA. Furthermore, this resulted in proportionately more correctly written words being produced. Fu and Ho (2010) sought to develop an intelligent and easy-to-use communication system, a Finger Language Recognition Subsystem, to help people with aphasia perform basic communication tasks naturally. This intelligent communication system has a data glove that inputs finger language components, a finger language recognition subsystem that recognizes the finger language components, and a virtual keyboard that produces text from the finger language components. Together these allowed the person to enter text into the virtual keyboard by wearing a data glove and making the appropriate finger gestures or use them to directly select the letters on the keyboard. While the authors demonstrated that manipulating the virtual keyboard using finger-language-based interaction techniques was possible, they did not test the system on any PWA.

3.3 Articles Using AI to Create Models of Lexicalization

Two other articles we reviewed used AI to create a model of lexicalization to simulate the naming error data of Finnish-speaking individuals (Järvelin et al, 2004; 2006). Production errors are of interest not only to understand the inner workings of the language production system but they also may help in diagnosis and treatment of various aphasia syndromes (van Hees et al., 2013). The authors tested the model on individuals with dementia (Finnish-speaking people with Alzheimer's disease (AD) or vascular dementia (VaD)) and healthy adults (2004) and also with Finnish-speaking PWA (2006). In both studies, the model was able to simulate word production errors in all groups, including individuals with four aphasic syndromes (anomic, Broca, conduction, and Wernicke) with a relatively high degree of accuracy.

3.4 Articles Using AI to Classify Paraphasic Errors

The two remaining articles both used AI to attempt to classify different types of paraphasias found in the utterances of PWA. However, they differed significantly in how they did this. While Fergadiotis and colleagues (2016) used written transcriptions of aphasic naming on the Philadelphia Naming Test (PNT) as their input to train and test their algorithms, Le and colleagues (2017) used ASR to recognize aphasic speech collected in the AphasiaBank databank as their input. While this made the process simpler for a clinician to potentially use, the model created by Le and colleagues was only able to discriminate between phonemic and neologistic errors while the one created by Fergadiotis and colleagues could discriminate between a larger number of paraphasic errors, namely formal, semantic, mixed, neologistic, and unrelated errors.

4. Discussion

The objective of this scoping review was to describe and synthesize knowledge on how AI is currently used in the language rehabilitation for people with aphasia and to better understand whether, and if so how, AI is being integrated into AAC devices or applications used in aphasia rehabilitation. To accomplish this, we performed a scoping review of the literature and found that, until recently, AI has been used mostly to diagnose and classify aphasia subtypes, with more than half of the studies focusing on this topic. However, we also observed that AI has been used to support aphasia therapy and, to a lesser degree, to create models of lexicalization and to classify paraphasic errors. As mentioned above, we found no articles that specifically addressed the use of AI in AAC for aphasia rehabilitation. Therefore, the discussion below focuses on the four themes identified above.

4.1 AI in AAC and Aphasia Therapy

While our search did yield articles that used an iPad^{TM} for aphasia rehabilitation, we did not find any articles that incorporated AI into AAC communication device designed specifically for aphasia rehabilitation. We also found articles that focused on AAC integrating AI for children with autism spectrum disorder or other complex communication needs, e.g. Farzana and colleagues (2021), who looked at AAC for children with autism spectrum disorder and found that integrating intelligent algorithms and analytics into AAC was beneficial for children's communication and required less cognitive and motor skills which, in turn, also lessened the demands of educators or caregivers. However, since our scoping review focused on adults with aphasia, we did not include articles addressing paediatric populations either. Furthermore, given our specific focus on aphasia, articles discussing the use of AI in AAC for adults with other communication problems, e.g. dysarthria, were also not included.

The lack of articles specific to AI for aphasia rehabilitation may be due to the lack of cross-talk between researchers in the domain of AI and those in aphasia rehabilitation. Consequently, the AI world has generally not focused on developing or improving upon AAC devices that could address the needs of people with aphasia. Light and colleagues (2019) state that multiple interactions and collaboration between disciplines are required for the development of communication tools that satisfy people with complex communication needs, including severe aphasia, and their families. Such an undertaking would require significant resources, including a considerable understanding of aphasia, access to PWA, large amounts of data (both aphasic and non-aphasic), along with new processing methodologies. The monetary resources required are also not negligible, especially when it is unclear whether there will be an uptake for such a device or technology. Currently the situation appears to be improving, with emerging communication and collaboration occurring between the two disciplines, which should, one day, lead to the possible incorporation of AI into novel AAC devices for PWA.

This recent increase in communication between the domains of aphasia rehabilitation and AI is already leading to AI being introduced into devices used for aphasia therapy. For example, Barbera and colleagues (2021) have created NUMA, an utterance verification system that uses a deep learning element and ASR to classify patients' attempts at naming words as being either 'correct' or 'incorrect'. This study, as well as others like it (i.e. Abad et al., 2013 and Le et al., 2018), no doubt benefited from information gained from previous studies on models of lexicalization and the classification of errors and demonstrate that ongoing conversations between researchers in AI and those in aphasia rehabilitation can lead to interesting innovations. One such innovation, namely the ability to recognize aphasic speech using automatic speech recognition (ASR) technology, will likely be of particular importance for the field of aphasia rehabilitation, once it has been perfected, since it can potentially both constitute a core component of novel AAC devices and be incorporated into systems that can be used for aphasia therapy. Another one of these innovations, algorithms that can evaluate PWA's output and provide feedback on its accuracy, are already making their way into systems that can be used for aphasia rehabilitation. To date, they are being used exclusively in research settings for practicing and providing feedback to PWA on naming exercises. While they have not yet been adapted to clinical settings, these experimental interventions may nevertheless enhance access to treatment and improve intensity. Further research is needed to assess the efficacy and acceptance of these systems by both SLPs and PWA. Furthermore, while these innovations have not yet been incorporated into the field of AAC, they may translate, with time and with more research, to AAC devices or applications. Here again, more research is needed to examine efficacy and acceptance, especially the level of comfort regarding the reliance on an AAC device or application that uses AI on a daily basis.

4.2 AI in the Diagnosis and Classification of Aphasic Syndromes

Given that one of the main strengths of AI in the health sector has been to improve the accuracy of disease diagnosis (Shen et al., 2019), we were not surprised to find that many of the articles we reviewed capitalized on this strength. An additional reason for this may be that the early efforts of the AI community have been primarily directed to an area where a specific interest had been expressed by those in the field of aphasia, namely, diagnosis of aphasia syndromes. The focus on diagnosis was facilitated by the availability of datasets comprising quantities of aphasic data that were sufficiently large to permit the development of diagnosis algorithms. For example, the creation of the dataset from the aphasia database based on the Aachen Aphasia Test (Axer et al., 2000c) has been essential for the development of diagnosis algorithms that we reviewed. While they may have an application for research purposes, it is possible that technologies that use AI for clinical diagnosis are, at least in their current iteration, less accessible clinically as they require expertise and training. Research to determine how to successfully implement these technologies is still needed if diagnosis algorithms are ever to make the leap to the clinic.

More recently the creation of the AphasiaBank database (MacWhinney et al., 2011) and its expansion to include different languages, such as Cantonese (Kong & Law, 2019), has not only been used to further develop diagnosis algorithms to languages other than English, but has also greatly contributed to research into developing ASR technology that will be able to recognize aphasic speech. Since AI is data driven, the continued contribution of aphasic data to the AphasiaBank database will most certainly lead to future breakthroughs in the field of AI and aphasia rehabilitation.

4.3 Strengths and Limitations

To our knowledge, this is the first scoping review examining how AI is applied in aphasia rehabilitation. One strength of this review is the inter-sectoral nature of our research team that uniquely included experts in the field of aphasia rehabilitation and in the field of AI, who could assess and understand the complexities of the AI technologies described in the articles.

This study should be considered in light of certain limitations. The date and language restrictions that were established in the initial search strategies as well as the six scientific databases that were selected may also have led to this review not comprising the full scope of literature available. Moreover, we considered articles or conference papers published in scientific journals (i.e., white literature) but did not consider any grey literature. This may also have resulted in some information being missed. Finally, while common when conducting scoping reviews (Pham et al., 2014), we did not assess the quality or validity of the included studies because the use of AI in aphasia rehabilitation is still a relatively novel area of research.

5. Conclusions

This scoping review provides an overview of the ways in which AI is used in the rehabilitation of PWA. The studies included in the review showed that the majority of research has used AI to assist with the diagnosis or classification of aphasia syndromes. However, more recently, AI has also developed methods for aphasia rehabilitation, more specifically for naming tasks. While AI still requires substantial advancements in order to be useful to SLPs, automatic speech recognition (ASR) technology that can reliably recognize aphasic speech is likely to be of particular importance to the field of aphasia rehabilitation since it has the potential (1) to be a central element for the creation of novel AAC devices or applications, and (2) to be incorporated into systems that will be used as part of innovative aphasia therapies. AI has not yet been integrated into clinical practice. If any use of AI is to make the transition to the clinic, new technologies or interventions that employ AI will need to be assessed to determine their efficacy and acceptance by both SLPs and PWA and their families.

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