Review Article

Artificial intelligence in assessment of neurogenic communication disorders in geriatric care: A literature review

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Abstract

Purpose: With medical advancements contributing to increased life expectancy, the growing geriatric population has heightened the need for speech–language pathology services to address neurogenic communication impairments. Artificial intelligence (AI) offers promising opportunities to augment care and meet this rising demand. The purpose of this review was to synthesize current evidence on the use of AI in assessing neurogenic communication disorders in older adults. By focusing on clinical applications such as automatic speech recognition (ASR) and related AI tools, this review highlights their potential to improve efficiency, accessibility, and accuracy in assessment, while also addressing challenges to successful clinical integration.

Materials and Methods: A literature review was performed using the keywords AI, ASR, aphasia, apraxia, and dysarthria on several databases, including PubMed, Google Scholar, and ASHA Journals Academy.

Results: This review summarizes current attempts at incorporating AI in automating the detection and diagnosis of neurogenic communication disorders, including dysarthria, aphasia, and apraxia of speech.

Conclusion: AI shows promise in the speech therapy field, in assisting with screening and evaluation of neurogenic communication disorders. However, clinical integration of these tools is challenging given their limitations with culturally and linguistically diverse datasets and concerns with ethical bias and data privacy.

Keywords: Artificial intelligence, geriatrics, speech therapy

Introduction

With the advancements in medical care, there has been a worldwide increase in human life expectancy. The percentage of people aged 60 years and older is projected to double globally in 2050, according to the World Health Organization ,(2022). In the U.S. Census Bureau ,(2024) reported a geriatric population of approximately 59.2 million in 2024, an increase of 9.4% since 2020. The Population Reference Bureau (2024) projects the number of people aged 65 years and older to increase by 47% by the year 2050. Similarly, in India, the United Nations Population Fund (UNFPA) India ,(2023) anticipates that individuals aged 60 years and above will comprise 20.8% of the total population by 2050, surpassing the number of children. As the geriatric population continues to grow, the demand for healthcare services is expected to rise substantially to address multiple chronic conditions that stem from aging (Khan, Addo, & Findlay, 2024).

Communication impairments in the geriatric population are often a consequence of diseases such as cerebrovascular accidents and neurodegenerative disorders (Zehnhoff-Dinnesen, Angerstein, & Deuster, 2010). In the United States, 25% of elderly community dwellers have some form of communication difficulty (Oshita, Gell, Stransky, Reed, & MacLean, 2023). Voice difficulties in the elderly are reported to be about 20%–47%, with speech and/or language difficulties as great as 70%–75% in the geriatric

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population in nursing homes (Zehnhoff-Dinnesen *et al*., 2010). Given the rising geriatric population and high prevalence rates of communication impairment among them, there is a growing need for efficient and accessible care to address these impairments for a better quality of life.

Speech–language pathologists (SLPs) play a vital role in assessing, diagnosing, and managing communication disorders. Their scope of practice also extends to prevention and wellness, as defined by the American Speech-Language-Hearing Association (2016). With the rapidly aging population, the demand for SLP services is steadily rising. Neurogenic communication disorders such as aphasia, dysarthria, and apraxia are particularly common among older adults, and their evaluation is often time-consuming, requiring detailed chart reviews, disorder-specific assessment batteries, and extensive interpretation (Mahmoud *et al*., 2023; Song et al., 2022; Wagner, Zusag, & Bloder, 2023). These challenges highlight the need for innovative approaches that can improve efficiency, accessibility, and accuracy in clinical care.

Artificial intelligence (AI) has emerged as a powerful tool in healthcare, contributing to health services management, early detection and diagnosis, predictive medicine, patient data analysis, and clinical decision-making (Secinaro, Calandra, Secinaro, Muthurangu, & Biancone, 2021). The field of speech-language pathology has begun to embrace AI, applying it to diagnostic assessments for speech, language, and swallowing, personalized treatment systems, interactive therapy games, chatbot conversational partners, virtual therapists, and intelligent assistants (Green, 2023; Zhang, Tang, Ding, & Zhang, 2024).

AI encompasses several subfields increasingly relevant to communication sciences and disorders (Deka, Shrivastava, Abraham, Nautiyal, & Chauhan, 2024). Machine learning (ML) uses algorithms that learn from data to make predictions or classifications, whereas deep learning (DL), a subset of ML, applies layered neural networks to process complex, high-dimensional data such as speech signals (Cordella, Marte, Liu, & Kiran, 2025; Mulfari, La Placa, Rovito, Celesti, & Villari, 2022). ML approaches can be broadly categorized into supervised and unsupervised learning. Supervised learning relies on labeled datasets in which input data are paired with known outputs, allowing models to learn direct mappings and make accurate predictions (Cordella *et al*., 2025). Unsupervised learning, by contrast, analyzes unlabeled data to uncover hidden patterns or clusters, which can be useful for identifying novel aspects of communication disorders. Automatic speech recognition (ASR), which converts spoken language into text, represents one of the most widely studied applications because of its direct clinical relevance for analyzing speech and language samples (Brahmi *et al*., 2024; Deka *et al*., 2024). Beyond ASR, AI applications include acoustic signal analysis of voice, natural language processing (NLP) for connected speech and discourse, and decision support systems that aid clinicians in diagnosis and treatment planning (Brahmi *et al*., 2024; Zhang *et al*., 2024). While AI applications are broad, this review focuses on approaches aimed at supporting clinical assessment in geriatric populations with neurogenic communication disorders. Although presbyphonia and other age-related voice changes represent an important area of study, they fall outside the scope of this review.

This review aimed to synthesize current research on AI applications in neurogenic communication assessments, with a focus on the geriatric population. Specifically, it examines the advantages and challenges of clinical integration of AI tools to clarify their role in improving accessibility, reducing clinician burden, and streamlining assessment practices in healthcare settings.

Materials and Methods

This literature review synthesized current evidence on the use of AI in the evaluation and diagnosis of neurogenic communication impairments in adults. Three electronic databases, PubMed, Google Scholar, and ASHA Journals Academy, were searched. PubMed was prioritized due to its refined Boolean search capabilities and indexing with Medical Subject Headings. Google Scholar was included to broaden coverage, whereas the ASHA Journals Academy was searched to ensure discipline-specific representation. Gray literature sources were not included in this review.

Search Strategy. The following Boolean search string was applied:

(aphasia OR dysarthria OR apraxia) AND (“artificial intelligence” OR “automatic speech recognition”).

Filters were applied to limit results to studies published in the last 5 years (January 2020–April 2025), with full-text availability, English language, human participants, and populations aged 19+ years, with an emphasis on adults aged 60 years and older.

Eligibility criteria

- **Inclusion criteria:** Peer-reviewed studies investigating the use of AI for evaluation or diagnosis of neurogenic communication impairments (aphasia, dysarthria, and apraxia of speech) in adults aged ≥60 years. Studies with broader adult age ranges (e.g., 30–70 years) were included if participants within the geriatric age group were represented.

- **Exclusion criteria:** Studies focused solely on algorithm development or model comparison without clinical application, studies in non-SLP domains (e.g., migraine, depression, and insulin regulation), and studies of dysphagia and voice, as this review centers on neurogenic communication skills. Pediatric populations and non-English publications were also excluded from the study.

Results

The literature search identified 18 studies examining applications of AI in the assessment and diagnosis of neurogenic communication impairments in adults aged 60 years and older. Four primary themes emerged from the synthesis:

1. ASR and NLP for impairment detection

ASR and NLP approaches aim to improve the understanding of disordered speech and provide objective metrics of impairment. Tetzloff *et al*. (2024) demonstrated that word error rate (WER) reliably distinguished patients with primary progressive apraxia of speech (PPAOS) from controls, correlating with severity ratings on the apraxia of speech rating scale. However, WER did not differentiate PPAOS subtypes, highlighting that ASR can detect the presence and severity of impairment but is limited for detailed subtype classification.

Šubert *et al.* ,(2025) applied ASR and NLP to spontaneous discourse in multiple system atrophy (MSA) and Parkinson's disease (PD), achieving high classification accuracy (area under the curve [AUC] = 0.81). Automated features revealed that MSA speech was marked by grammatical abnormalities, phrase repetitions, slower articulation, and longer pauses, demonstrating AI's ability to detect nuanced language impairments in naturalistic speech contexts.

Commercial off-the-shelf ASR systems (Google Cloud and Microsoft Azure) performed moderately for early or mild impairments, indicating the need for task-specific or tailored models (Gutz, Stipancic, Yunusova, Berry, & Green, 2022; Mahmoud *et al*., 2023). Notably, ASR sometimes outperformed human listeners in early dysarthria detection in PD (Moya-Galé, Walsh, & Goudarzi 2022).

Semi-supervised ASR approaches have also been applied to aphasia. Torre, Romero, and Álvarez (2021) reduced WER by 25% in English aphasic speech and developed the first Spanish-language aphasia ASR system using under 1 h of patient data. Rezaii *et al*. (2024) applied large language models to categorize primary progressive aphasia (PPA) subtypes, achieving 88.5% alignment with consensus classifications of non-variant/agrammatic, semantic, and logopenic, and uncovering variant-specific linguistic features.

2. ML and acoustic biomarkers for disorder classification

Several studies leveraged acoustic features and ML to classify disorders and quantify severity. Dubbioso *et al*. (2024) developed a decision tree model for ALS-related dysarthria, achieving 86.6% accuracy across nondysarthric, mild, moderate, and severe cases. Tena, Clarià, Solsona, and Povedano (2023) used an acoustic voiceprint to detect bulbar dysfunction in ALS, reaching 91% accuracy after semi-supervised re-labeling, surpassing clinician judgment and demonstrating utility in early detection.

Song *et al*. (2022) applied a DL algorithm to differentiate ataxic and hypokinetic dysarthria in Parkinsonian and cerebellar ataxia patients. The model outperformed neurology resident doctors, achieving AUC > 0.95 for differentiating dysarthria types and ≥0.85 for dysarthria versus normal speech. Zhang *et al*. (2023) validated an AI-powered acoustic system within a clinical decision support system for Wilson's disease, distinguishing healthy, mild, and moderate–severe dysarthria with an AUC > 80% across tasks including sustained phonation, diadochokinesis, and *S*/*Z* ratio.

Connected and naturalistic speech analyses were central to several studies. Svoboda *et al*. (2022) applied ML to connected speech in multiple sclerosis, achieving 82% accuracy (AUC = 0.76) in differentiating patients from controls, capturing subtle vocal impairments. Isaev *et al.* ,(2023) showed that vowel-based acoustic features reliably marked early ataxic dysarthria. Illner *et al*. (2022) demonstrated that automated articulation rate analysis in spontaneous monologs and reading passages reliably identified slowed speech in idiopathic REM sleep behavior disorder (iRBD), PD, and MSA, with Google & Pyphen algorithms achieving correlations to human ratings of 0.95–0.99 on Pearson's correlation coefficient (r) and low error rates. Slower speech in MSA and trends in iRBD suggest that articulation rate may serve as a biomarker for early and progressive neurodegeneration.

These studies collectively indicate that AI-driven acoustic analysis, especially with connected speech, provides sensitive, objective markers for diagnosis, severity assessment, and progression monitoring.

3. Language profiling and aphasia classification

AI and NLP tools can support aphasia assessment and linguistic profiling. Semi-supervised ASR models reduce transcription errors and enable low-resource language applications (Torre *et al*., 2021). Rezaii *et al.* ,(2024) demonstrated that large language models can classify PPA subtypes while identifying distinctive linguistic markers, highlighting AI's potential to supplement diagnostic decision-making and provide novel insights into language impairment. NLP pipelines like Batchalign (Liu, MacWhinney, Fromm, & Lanzi, 2023) can reduce transcription and analysis time by 75%, increasing accessibility to automated language profiling. In addition to automating language analysis, several studies have explored AI-driven approaches for quantifying aphasia severity. Jothi, Yawalkar, and Mamatha (2021) developed a speech assessment system using ML and neural network models to classify aphasic speech into mild, moderate, and severe categories based on acoustic and textual features, achieving high accuracy. Similarly, Nivedha, Chandrasekar, and Jothi (2023) introduced a hybrid DL model, which classified aphasia severity with 98.1% accuracy. Together, these studies demonstrate the feasibility of automated speech-based severity analysis, supporting more objective and scalable aphasia assessment.

Generative AI has also been explored to create clinical resources. Pierce (2024) used DALL-E 2 to generate images for aphasia assessment tasks, successfully producing 94.5% of targets. Single-word stimuli were most reliable, while sentence-level prompts revealed challenges in handling complex syntax. These tools provide low-cost, customizable support for assessment and therapy planning, although clinician oversight remains essential.

4. Integration of multimodal features for clinical decision support

Several studies combined multiple acoustic and linguistic features within decision support systems to enhance diagnostic accuracy. For instance, Zhang *et al*. (2023) demonstrated that integrating acoustic features into a clinical decision support system allowed clinicians to assess dysarthria severity in Wilson's disease reliably, supporting early detection and monitoring. Similarly, AI models incorporating both acoustic and linguistic parameters improved discrimination between MSA and PD (Subert *et al*. 2025) and provided objective measures that complement clinical judgment. These approaches exemplify the potential for AI to serve as a bridge between technological innovation and practical clinical implementation [Table 1].

Table 1: AI in neurogenic communication disorders: Study summary

Study	Disorder/population/ sample size	AI method	Task type	Key findings
Tetzloff *et al*. (2024)	Primary progressive apraxia of speech (PPAOS; 45 patients with PPAOS + 22 controls)	ASR—word error rate (WER) analysis	Reading/connected speech	WER distinguished PPAOS from controls and correlated with severity; not reliable for subtype classification
Šubert *et al*. ,(2025)	Multiple system atrophy (MSA) and Parkinson's disease (PD; 39 MSA + 39 PD + 39 controls)	ASR + NLP	Spontaneous discourse (connected speech)	Automated linguistic features distinguished MSA from PD; strong agreement with manual
Gutz *et al*. (2022)	Amyotrophic lateral sclerosis (ALS; 52 ALS +20 controls)	Off-the-shelf ASR (Google Cloud)	Connected speech	Moderate correlation with SLP severity ratings; poor sensitivity to mild/early bulbar involvement; OTS limitations highlighted
Mahmoud *et al*. (2023)	Aphasia (12 aphasia + 34 controls)	Off-the-shelf ASR (Microsoft Azure, Google)	Aphasia assessment tasks	OTS ASR underperformed versus deep neural networks for aphasia; Azure performed relatively better
Moya-Galé *et al.* ,(2022)	Parkinson's disease (PD; 20 PD + 20 controls)	Web-based ASR (Google Cloud)	Sentence reading in noise (100 sentences)	ASR matched human specificity for controls (75%) and showed higher sensitivity for dysarthria (60% vs. 45% human)
Torre *et al*. (2021)	Aphasia (AphasiaBank (English) + <1 h Spanish person with aphasia data)	Semi-supervised E2E ASR (wav2vec2.0)	Connected speech (read and spontaneous)	25% relative WER reduction in English; first Spanish aphasia ASR with <1 h data; data augmentation improved performance
Rezaii *et al.* ,(2024)	Primary progressive aphasia (PPA; 78 PPA patients)	Large language models (LLMs), unsupervised clustering	Spontaneous language samples	LLMs identified three clusters aligning with consensus PPA subtypes (88.5% agreement); highlighted variant-specific linguistic markers
Liu *et al*. (2023)	Aphasia (Aphasia Bank—11 patients with semantic dementia + 17 patients with progressive nonfluent aphasia + 23 controls)	Batchalign NLP pipeline (transcription + morphosyntactic analysis)	Connected speech samples	Reduced transcription time by ~75%, expanding access to automated language profiling

Table 1. Continued

Study	Disorder/population/ sample size	AI method	Task type	Key findings
Dubbioso *et al*. (2024)	ALS (74 ALS +23 controls)	Decision tree classifier (acoustic features)	Eleven speech tasks (vowels, syllables, reading, and picture description)	86.6% accuracy classifying non-dysarthric to severe dysarthria; identified novel acoustic markers; some misclassifications in non-dysarthric/controls
Tena *et al*. (2023)	ALS—bulbar dysfunction (45 ALS + 18 controls)	Voiceprint (machine learning; random forest + semi-supervised)	Sustained vowels (five Spanish vowels)	Random forest 88.3% accuracy (bulbar vs. control); SVM re-labeling improved bulbar versus non-bulbar classification to 91.0% accuracy
Song *et al*. (2022)	Ataxic and hypokinetic dysarthria (Parkinsonian and cerebellar; 76 controls + 112 ataxia + 207 hypokinetic)	Deep learning	Reading passage (autumn) + rapid counting	AUC > 0.95 for ataxic versus hypokinetic; ≥0.85 for dysarthria versus normal; outperformed resident doctors; better performance on longer reading task
Zhang *et al*. (2023)	Wilson's disease (WD) (dysarthria severity; 65 WD patients + 65 controls)	AI-powered acoustic analysis in a clinical decision support system	Sustained phonation, DDK, and *S/Z* ratio	AUC > 80% for classifying healthy, mild, moderate–severe; DDK was most discriminative; system scalable and reproducible
Svoboda *et al*. (2022)	Multiple sclerosis (MS) 65 MS patients + 66 controls	Machine learning on connected speech acoustic features	Connected speech recordings (precise phoneme segmentation)	Accuracy 0.82 (AUC = 0.76); detected MS-related vocal changes from natural speech
Isaev *et al*. ,(2023)	Ataxic dysarthria (61 ataxia + 25 controls)	Deep learning for vowel segmentation and acoustic metrics	Connected speech	Average vowel entropy (AVE) and mean intensity standard deviation (MISD) distinguished ataxia, including mild cases; AVE correlated with clinical Brief Ataxia Rating Scale scores and progression; Mean pitch standard deviation was not discriminative
Illner *et al*. (2022)	Idiopathic Rapid Eye Movement Behavior Disorder (iRBD), PD, MSA (25 iRBD + 25 PD + 20 MSA+ HCs)	Automated articulation rate algorithms (Google & Pyphen and Praat)	Spontaneous monolog and word reading	Google & Pyphen are highly correlated with human ratings (r = 0.95–0.99); they detected slowed articulation in MSA and trends in iRBD; Praat is better for MSA
Jothi *et al*. (2021)	Aphasia (Aphasia Bank—60 Broca + 75 Anomic + 49 Conduction +10 Transmotor +19 Wernicke + 24 controls)	Multiple machine learning models comparison	Connected speech samples	Demonstrated high accuracy in predicting aphasia severity levels. Accuracy differed depending on the model used
Nivedha *et al*. (2023)	Aphasia (91 patients with aphasia)	Hybrid deep learning model	Connected speech samples	Classified aphasia severity with 98.1% accuracy
Pierce (2024)	Aphasia (stimulus generation)	Generative AI—DALL·E 2 (text-to-image)	Stimulus generation for naming and sentence tasks	200 target images attempted—189 images (94.5%) generated; efficient and low-cost for single-word items; sentence-level images more challenging

AI = artificial intelligence, ASR = automatic speech recognition, PPAOS = primary progressive apraxia of speech, NLP = natural language processing, MSA = multiple system atrophy, PD = Parkinson's disease, PPA = primary progressive aphasia, ALS = amyotrophic lateral sclerosis, AUC = area under the curve, r = Pearson's correlation coefficient.

Studies are listed in the order they appear in the results

Discussion

This review synthesizes current research on AI applications in the assessment and monitoring of neurogenic communication disorders in older adults, highlighting the incorporation of AI for impairment detection, disorder classification, language profiling, and aphasia classification, and clinical decision support. Across studies, AI demonstrates considerable potential to complement clinician assessment by providing objective, quantifiable measures of speech and language impairment; however, significant challenges remain in terms of generalizability, naturalistic contexts, and clinical integration.

ASR and NLP systems have been widely investigated for their ability to detect impairments and generate objective metrics. Tetzloff *et al*. (2024) demonstrated that ASR-derived WER reliably distinguished patients with PPAOS from healthy controls and correlated with severity, though it did not differentiate PPAOS subtypes. Similarly, Subert *et al*. (2025) applied ASR and NLP to spontaneous discourse in MSA and PD, achieving high classification accuracy and identifying specific linguistic features of MSA speech, such as grammatical errors, phrase repetitions, slower articulation, and longer pauses.

ML applied to acoustic features has produced reliable biomarkers for dysarthria classification, severity grading, and disease monitoring. Dubbioso *et al*. (2024) used decision tree models to classify ALS-related dysarthria into four severity levels with 86.6% accuracy, while Tena *et al*. (2023) developed an acoustic voiceprint model that detected bulbar dysfunction in ALS, surpassing clinician judgment. Song *et al*. (2022) implemented a DL model to classify ataxic and hypokinetic dysarthria in patients with Parkinsonian disorders and cerebellar ataxia, outperforming neurology residents in differentiating subtypes and detecting dysarthria versus normal speech. Zhang *et al*. (2023) validated an AI-powered acoustic analysis system within a clinical decision support system for Wilson's disease, successfully distinguishing healthy, mild, and moderate–severe dysarthria across structured tasks. Connected and naturalistic speech studies further demonstrate AI's utility in classifying disorders, as demonstrated by Svoboda *et al*. (2022) with multiple sclerosis patients and by Illner *et al*. (2022) with patients with idiopathic REM sleep behavior disorder, PD, and MSA. These studies validate AI's potential in supporting the identification of early biomarkers of neurodegeneration.

AI has also been applied to language profiling and aphasia assessment, both for subtype classification and assessment efficiency. Torre *et al*. (2021) used a semi-supervised algorithm to improve recognition in English and Spanish aphasic speech, achieving a 25% reduction in WER and enabling model development with less than 1 h of patient data in Spanish. Rezaii *et al*. (2024) employed large language models to categorize PPA subtypes while identifying variant-specific linguistic deficits. NLP pipelines such as Batchalign (Liu *et al*., 2023) reduced transcription and analysis time, broadening access to automated language profiling. Recent work on automated severity classification shows promising results, with Jothi *et al*. (2021) and Nivedha *et al*. (2023) reporting high accuracy in predicting aphasia severity from acoustic and linguistic features. These studies highlight AI's potential to provide objective, data-driven insights that complement clinician-led assessment. Generative AI approaches, including DALL-E 2 (Pierce, 2024), have shown feasibility in generating visual stimuli for aphasia assessment, with high success rates for single-word tasks, although sentence-level prompts require careful design and clinician oversight.

The integration of these modalities in clinical decision support systems demonstrates the potential for AI to improve accuracy, consistency, and efficiency (Zhang *et al*., 2023). Importantly, AI provides distinct advantages in clinical settings. It can accelerate evaluation and diagnosis, reduce clinician workload, support inter-rater reliability, and improve accessibility to care, particularly in areas with SLP shortages (Zhang *et al*., 2024). With ongoing shortages in the field of speech-language pathology, especially in rural regions, AI can help reduce wait times by enabling faster assessments and more timely diagnoses. This, in turn, supports prompt treatment referrals and ultimately leads to improved patient outcomes.

Despite these advantages, important challenges remain. Many studies highlight that AI systems still struggle with natural conversational speech, early or mild impairments, and use with culturally and linguistically diverse populations (Gutz *et al*., 2022; Tobin *et al*., 2024; Torre *et al*., 2021). As a result, clinician oversight remains essential to integrate findings from chart reviews, case history, evaluation results, and clinical observations for accurate diagnosis, counseling, and decision-making. Ethical concerns such as data privacy, Health Insurance Portability and Accountability Act compliance, risks of re-identifying de-identified data, and the need for informed patient consent also require careful attention when applying AI in healthcare (Li, Ruijs, & Lu, 2023; Murdoch, 2021; Naik *et al*., 2022). Moreover, most AI systems have not yet been validated in real-world clinical workflows, underscoring the need for further research and rigorous testing before widespread clinical adoption.

Future directions in this field should emphasize the development of clinically interpretable, scalable, and multimodal AI systems, leveraging interdisciplinary collaboration between engineers and SLPs. Efforts to include diverse datasets, evaluate longitudinal outcomes, and enhance usability and training for clinicians will be essential for successful integration into practice (Bhimani, 2025; Cordella *et al*., 2025). While the literature reviewed here represents a promising foundation, the field is still emerging. Nevertheless, AI offers a complementary toolset to augment clinician assessment, enabling earlier detection, more precise monitoring, and potentially more timely interventions for neurogenic communication disorders in older adults.

Conclusion

With a growing geriatric population, the integration of AI into the evaluation and diagnosis of communication impairments offers the potential to improve access to timely care and reduce clinician burden. Extensive research has been conducted on automating evaluations for neurogenic communication disorders, with particular emphasis on dysarthria and aphasia. These efforts include impairment detection, disorder classification, and clinical decision support. Overall, recent studies have demonstrated improved accuracy of AI algorithms in detecting and diagnosing neurogenic communication impairments. However, clinical integration remains limited due to ethical concerns, a lack of cultural and linguistic diversity in training datasets, and challenges related to data privacy. Furthermore, processes for clinician oversight, training, patient education, and informed consent need to be streamlined before widespread clinical implementation.

There is clear potential for AI integration in clinical SLP settings, provided it is approached with cautious and deliberate steps. While there is also growing research and interest in the use of AI in SLP treatment, this study focuses solely on its role in evaluation.

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Data availability statement

The data sets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Conflicts of interest

There are no conflicts of interest.

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