

How Is AI Being Used Across Communication Disorders? A Review of the Research

2026 NJSHA Convention Presentation Handout

Siena Sun, Mengyang Qiu, Sara NassrElgrgaw
Department of Speech-Language Pathology
Saint Elizabeth University, Morristown, NJ

Contents

1	Introduction	1
2	Aims	2
3	Method	2
3.1	Study Design and Paper Selection	2
3.2	Analysis Plan	3
4	Results	4
4.1	Language Disorders (Aphasia)	6
4.2	Motor Speech Disorders (Dysarthria, Apraxia)	8
4.3	Fluency Disorders (Stuttering)	10
4.4	Swallowing Disorders (Dysphagia)	12
4.5	Voice Disorders	14
5	Discussion	16

1 Introduction

Communication disorders research has long been multidisciplinary in nature, drawing on speech-language pathology, neuroscience, psychology, and other fields concerned with human communication and behavior. With advances in artificial intelligence (AI)—from traditional machine learning approaches to more recent deep learning architectures, automatic speech recognition (ASR) systems, and large language models (LLMs)—researchers from computer science and engineering have increasingly contributed to the assessment, diagnosis, and treatment of communication disorders.

While several recent scoping reviews have summarized applications of AI in specific areas of communication disorders, these reviews tend to focus on journal publications and do not comprehensively cover computer science and AI conference proceedings, where conference papers are a central mode of scholarly communication [1]. Moreover, no review to date has systematically examined AI applications across multiple communication disorder types, including language disorders (aphasia), motor speech disorders (dysarthria, apraxia of speech), fluency disorders (stuttering), swallowing disorders (dysphagia), and voice disorders, within a unified analytical framework. As a result, the structure of this rapidly growing research landscape and the relationships between computer science and clinical research communities remain incompletely characterized.

This gap poses practical challenges for clinicians, researchers, and educators. For clinicians seeking to integrate AI-based tools into evidence-based practice, the literature is scattered across venues that differ in accessibility, terminology, and research conventions. For researchers, persistent disciplinary boundaries may limit collaboration and slow translational progress. For educators, the lack of a comprehensive map of this landscape makes it difficult to prepare students for an increasingly AI-informed clinical field. In the present study, we apply natural language processing and network science methods to publication abstracts to analyze and visualize the research landscape of AI across communication disorders, with the goal of making this interdisciplinary and rapidly evolving field more accessible and navigable.

2 Aims

The present study has two primary aims. First, we aim to provide a comprehensive map of AI research across five major areas of communication disorders—language disorders, motor speech disorders, fluency disorders, swallowing disorders, and voice disorders—by increasing the mutual visibility of work published in computer science and non-computer science venues, thereby facilitating interdisciplinary collaboration. Second, using network science measures, we aim to identify publications that are densely connected to many other studies within each disorder area, which may serve as effective entry points for clinicians, researchers, and educators seeking to engage with AI applications in communication disorders.

3 Method

3.1 Study Design and Paper Selection

This study employed a scoping review methodology to systematically map the existing literature on the application of AI in the assessment and treatment of communication disorders. The review was conducted in accordance with the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews) guidelines to ensure methodological rigor and transparency.

Search Strategy A comprehensive literature search was conducted using the Omni library search system, which aggregates records from multiple electronic databases including Scopus, ProQuest Central, PubMed, Springer Nature, Nursing and Allied Health, and IEEE. To ensure coverage of computer science venues where conference proceedings are a primary mode of scholarly communication, additional searches were conducted in the ACL Anthology (Association for Computational

Linguistics conference proceedings) and the ISCA Archive (Interspeech conference proceedings).

The search strategy combined the following terms:

(artificial intelligence OR AI OR speech recognition OR natural language processing OR NLP OR deep learning OR machine learning OR language model OR language models OR LLM OR LLMs) AND (communication disorder OR communication disorders OR language disorder OR language disorders OR speech disorder OR speech disorders OR voice disorder OR voice disorders OR aphasi OR apraxi* OR dysarthri* OR stutter* OR swallow* OR dysphagi*)*

Searches were limited to studies published between 2010 and 2025 to capture contemporary developments in AI technologies.

Eligibility Criteria and Screening Eligibility criteria were established using the PCC (Population–Concept–Context) framework, as recommended by PRISMA-ScR. Studies were included if they met all of the following criteria:

- (a) **Population:** The study focused on individuals with communication disorders, including language disorders, motor speech disorders, fluency disorders, voice disorders, or swallowing disorders.
- (b) **Concept:** The study utilized AI methodologies such as machine learning, deep learning, speech recognition, natural language processing, neural networks, or language models.
- (c) **Context:** The study was conducted in clinical, educational, or research contexts relevant to speech-language pathology, including screening, assessment, diagnosis, intervention, treatment monitoring, assistive or augmentative communication technologies, and clinical decision support.

Eligible sources included peer-reviewed journal articles and conference proceedings published in computational venues (i.e., IEEE, ACL, ACM, Interspeech). Studies were excluded if they were non-peer-reviewed, were review articles, lacked accessible abstracts, or were not clinically relevant.

All identified records underwent a structured screening process:

- (a) Two independent reviewers screened titles and abstracts using the eligibility criteria.
- (b) Studies deemed relevant or potentially relevant were advanced to further analysis.
- (c) Discrepancies were resolved through discussion, with a third reviewer consulted when consensus could not be reached.

Included articles were categorized into five disorder areas: language disorders (aphasia), motor speech disorders (dysarthria, apraxia of speech), fluency disorders (stuttering), swallowing disorders (dysphagia), and voice disorders.

3.2 Analysis Plan

To explore thematic patterns across disorder areas, we applied keyword extraction and network analysis methods to the abstracts of all included publications.

Keyword Extraction We extracted key terms from each abstract using a two-stage approach that combines embedding-based keyword identification with LLM refinement, implemented through the KeyBERT library [2]. The pipeline is shown in Figure 1.

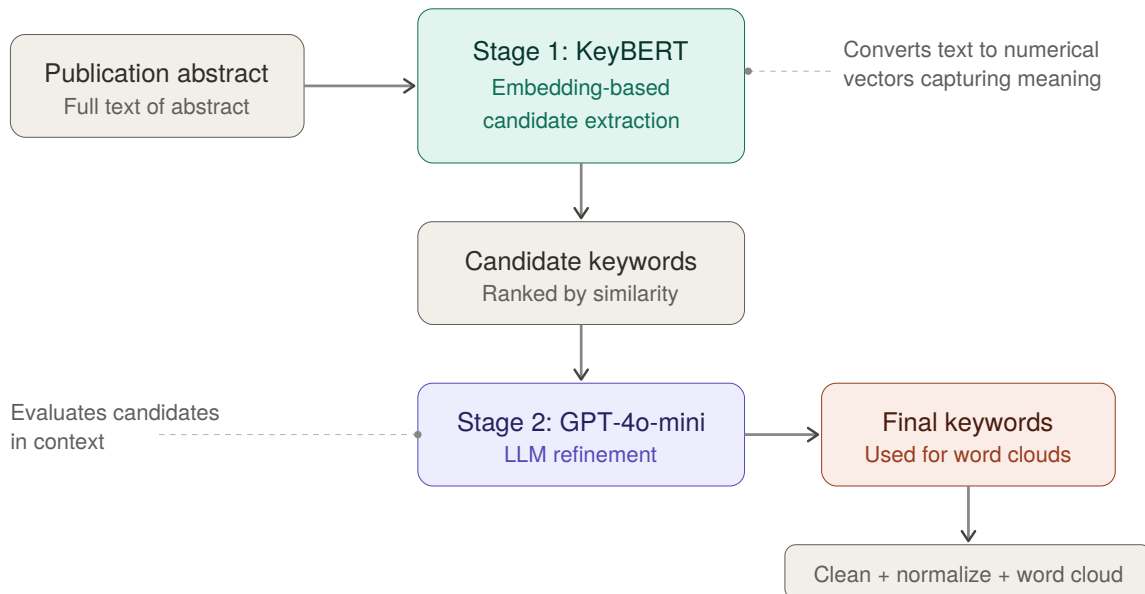


Figure 1: The two-stage KeyBERT + KeyLLM keyword extraction pipeline.

Network Analysis We constructed semantic networks of publication abstracts for each disorder area to visualize the overall research landscape and identify thematically central publications. Each abstract was encoded as a semantic embedding, a numerical representation capturing its overall meaning, using the SentenceTransformers framework [3]. We then computed pairwise cosine similarity between all abstracts (see Figure 2) and applied the Triangulated Maximally Filtered Graph (TMFG) method [4] to filter out weak connections, producing an unweighted network where nodes represent publications and edges represent high semantic similarity. Community detection was performed using the Leiden algorithm to identify clusters of thematically related publications. Within each community, we identified the publication with the highest degree—the number of connections to other articles—as the most thematically central entry point for that cluster.

4 Results

The systematic search yielded a total of 3,619 records across all sources. After removal of duplicates, screening, and application of the eligibility criteria, 1,173 articles were retained for analysis. These were classified into five disorder areas based on their primary focus: Language Disorders (Aphasia; $n = 158$), Motor Speech Disorders (Dysarthria, Apraxia; $n = 401$), Fluency Disorders (Stuttering; $n = 138$), Swallowing Disorders (Dysphagia; $n = 216$), and Voice Disorders ($n = 260$).

Figure 3 presents publication trends across the five disorder areas from 2010 to 2025. All areas show substantial growth in recent years, with a particularly sharp increase beginning around 2018. Motor speech disorders consistently account for the largest share of publications, followed by voice disorders and swallowing disorders. Language disorders and fluency disorders, while smaller in

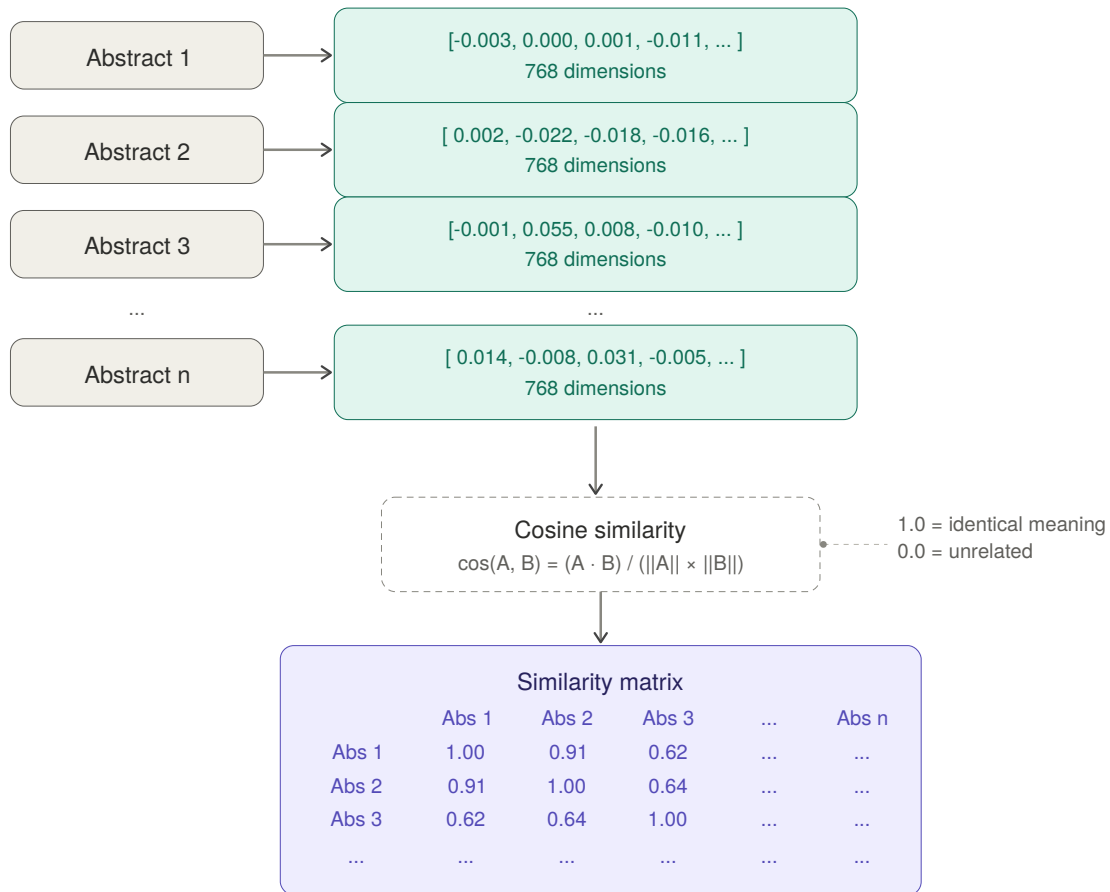


Figure 2: Illustration of the embedding and similarity computation steps in the network analysis pipeline. Each abstract is encoded as a 768-dimensional numerical vector, and cosine similarity is computed between all pairs to produce a similarity matrix.

volume, also show clear upward trajectories. By 2025, all five areas reached their highest annual publication counts, reflecting the accelerating interest in AI applications across communication disorders.

In the following subsections, we present results for each disorder area, including keyword word clouds highlighting prominent research themes, semantic network visualizations showing community structure, and a table identifying the highest-degree publication within each community cluster as a recommended entry point for readers.

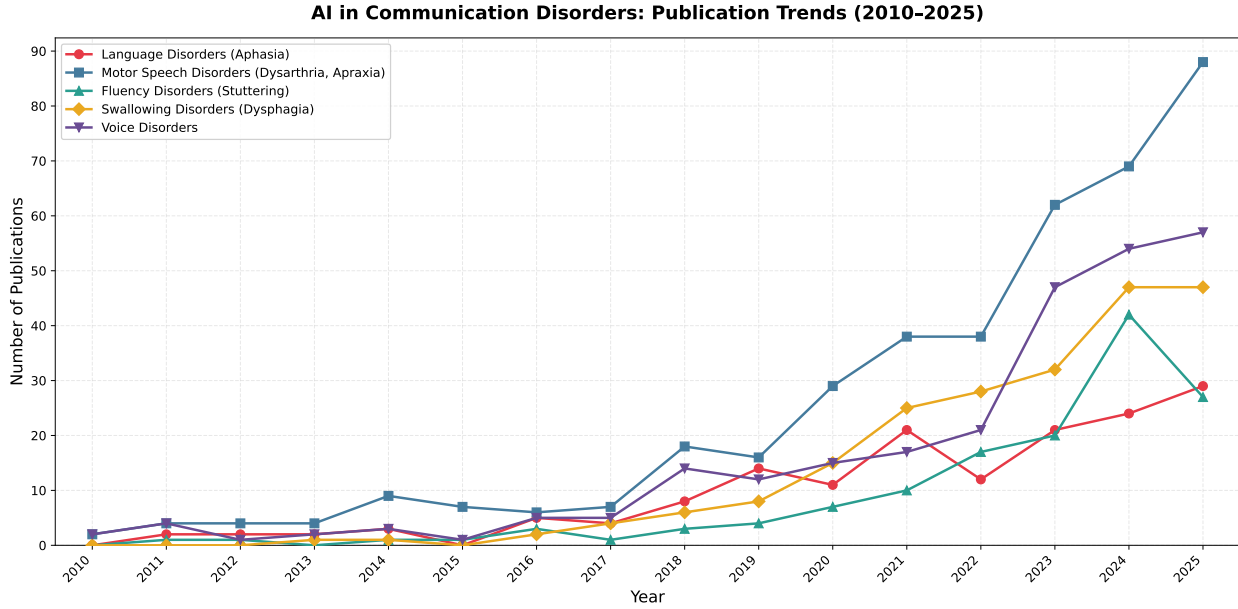


Figure 3: AI in Communication Disorders: Publication Trends (2010–2025).

4.1 Language Disorders (Aphasia)

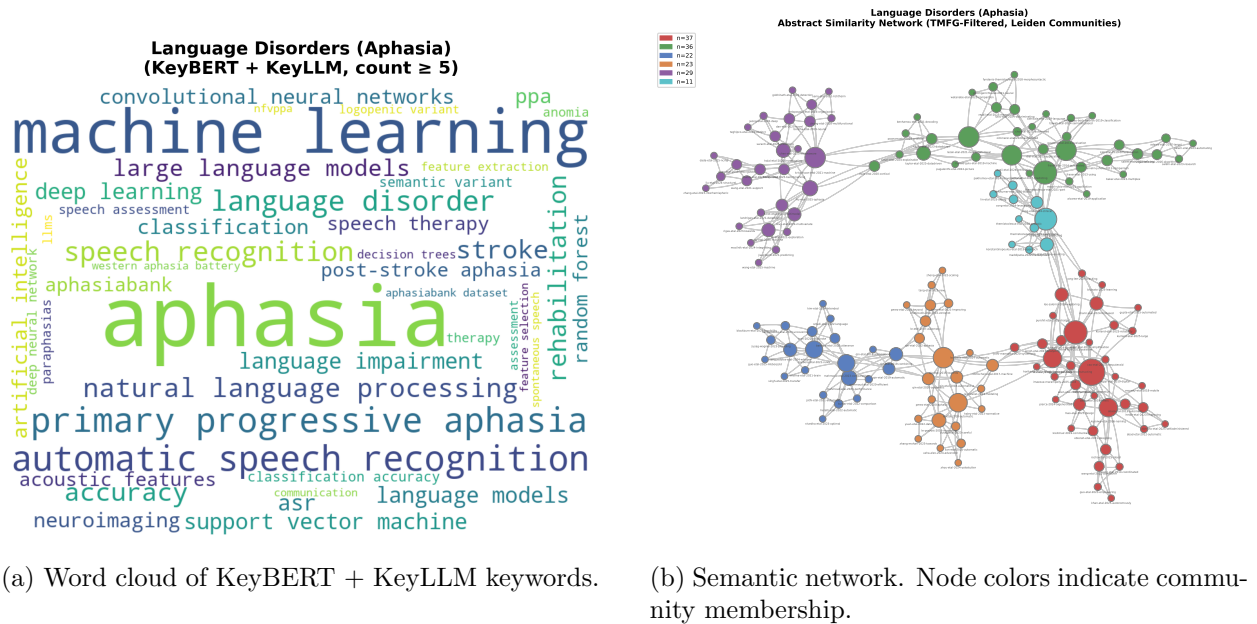


Figure 4: Language Disorders (Aphasia): keyword word cloud (a) and abstract similarity network (b).

Table 1: Highest-degree publications per community cluster: Language Disorders (Aphasia).

Cluster	Publication	Year	Degree
1	Generative AI applied to AAC for aphasia: a pilot study of Aphasia-GPT [5] <i>Keywords:</i> aphasia, augmentative and alternative communication, aac system, aphasia-gpt, natural language processing, mobile web app, language sampling, sentence production aid, non-fluent aphasia, communication support, user feedback, pilot testing, communication tasks, phonemic paraphasias, apraxic errors, intelligible speech	2025	21
2	Part of Speech Production in Patients With Primary Progressive Aphasia: An Analysis Based on Natural Language Processing [6] <i>Keywords:</i> primary progressive aphasia, ppa variants, nonfluent ppa, logopenic ppa, semantic ppa, part of speech, pos production, morphological markers, machine learning, classification analysis, natural language processing, content words, function words, distinguishing features, elaborative speech elements, adjectives, adverbs	2021	18
3	NUVA: A Naming Utterance Verifier for Aphasia Treatment [7] <i>Keywords:</i> anomia, aphasia, language disorder, stroke, speech performance, picture naming tasks, assessment, speech and language therapists, automatic speech recognition, artificial intelligence, deep learning, nuva, utterance verification system, naming attempts, accuracy, cross-validation, slt ratings	2021	13
4	Towards automatic assessment of aphasia speech using automatic speech recognition techniques [8] <i>Keywords:</i> aphasia, automatic speech recognition, asr, language impairment, brain injury, cantonese, speech analysis, acoustic models, language models, recognition performance, natural oral discourses, supra-segmental duration, linguistic content, assessment, speech recognition	2016	16
5	Machine learning-based multimodal prediction of language outcomes in chronic aphasia [9] <i>Keywords:</i> neuroimaging, aphasia, machine learning, multimodal, support vector regression, functional magnetic resonance imaging, diffusion mri, cerebral blood flow, lesion load, language measures, prediction accuracy, stroke, neurobiological substrates, western aphasia battery, complementary information	2021	16
6	Predicting Severity in People with Aphasia: A Natural Language Processing and Machine Learning Approach [10] <i>Keywords:</i> speech language pathologists, aphasia, natural language processing, machine learning, severity assessment, discourse elicitation, regression models, classification model, deep neural network, random forest, accuracy, rehabilitation, clinicians, therapy, pwa, language features, clustering, severity levels	2021	17

Continued from previous page

Cluster	Publication	Year	Degree
	<i>Keywords:</i> dysarthric speech, automatic speech recognition, scoping review, acoustic features, acoustic models, deep learning, convolutional neural network, deep neural networks, recurrent neural networks, speech data, generalization applicability, speaker-dependent issues		
5	Dysarthric Speech Recognition Using Kullback-Leibler Divergence-Based Hidden Markov Model [15]	2016	9
	<i>Keywords:</i> dysarthria, speech disorder, speech recognition, phonetic variation, kullback-leibler divergence, hidden markov model, emission probability, categorical distribution, phoneme posterior probabilities, deep neural networks, experimental evaluation, gaussian mixture models		
6	Dysarthric Speech Recognition using Depthwise Separable Convolutions: Preliminary Study [16]	2023	16
	<i>Keywords:</i> dysarthria, speech impairments, automatic speech recognition, asr, dysarthric speech recognition, dsr, speech vision, acoustic models, separable convolutional neurons, word recognition accuracy, dysarthric speech intelligibility, ua-speech, depthwise separable architecture		
7	The relationship between perceptual disturbances in dysarthric speech and automatic speech recognition performance [17]	2016	22
	<i>Keywords:</i> automatic speech recognition, dysarthric speech, acoustic variability, perceptual disturbances, asr performance, articulatory precision, prosody, speech analysis, dysarthria subtypes, speech recognition technology		
8	Efficacy of Current Dysarthric Speech Recognition Techniques [18]	2023	33
	<i>Keywords:</i> speech recognition, dysarthric speech recognition, speech and language technology, dysarthria, character extraction, mel frequency cepstral coefficients, linear predictive coding, perceptual linear prediction, gammatone frequency cepstral coefficients, formant re-synthesis, acoustic space manipulation, speech intelligibility, deep learning, speaker model, lexical models, data gathering, noise interference, specialist models, variances in speech, assistive technology, multimodal approaches, feature extraction, user accessibility		
9	Homogeneous Speaker Features for on-the-Fly Dysarthric and Elderly Speaker Adaptation and Speech Recognition [19]	2025	13
	<i>Keywords:</i> asr technologies, dysarthric speech, elderly speech, data-efficient methods, speaker-level features, test-time adaptation, dnn, tdnn, conformer models, variance-regularized spectral basis embedding, feature-based learning, hidden unit contributions, uaspeech, torgo, dementiabank, cantonese jccocc, error rate reduction, real-time factors, speaker-level homogeneity, t-sne visualization		
10	Deep neural network architectures for dysarthric speech analysis and recognition [20]	2021	14
	<i>Keywords:</i> deep neural networks, dysarthric speech, convolutional neural network, long short-term memory, speech recognition, mel-frequency cepstral coefficients, mel-frequency spectral coefficients, perceptual linear prediction, hidden markov model, gaussian mixture models, recognition rate		
11	An Investigation to Identify Optimal Setup for Automated Assessment of Dysarthric Intelligibility using Deep Learning Technologies [21]	2023	16

Continued on next page

Continued from previous page

Cluster	Publication	Year	Degree
	<i>Keywords:</i> dysarthria, deep learning, intelligibility assessment, classification accuracy, evaluation strategies, speech intelligibility, generalization, dysarthric speakers, clinical applications, benchmarking		
12	Dysarthria Detection with Deep Representation Learning for Patients with Parkinson’s Disease [22] <i>Keywords:</i> dysarthria, parkinson’s disease, speech analysis, machine learning, detection models, speech dataset, remote data acquisition, deep representation learning, classification methods, automated self-monitoring, disease management	2024	14
13	Next-Gen Speech Disorder Diagnostics: CNN Methods for Dysarthria Classification [23] <i>Keywords:</i> neurological disorders, amyotrophic lateral sclerosis, cerebral palsy, dysarthria, communication capacity, early diagnosis, effective therapies, convolutional neural network, cnn, torgo database, speech categorization, deep learning technology, dysarthric individuals, non-dysarthric individuals, accuracy, diagnostic capabilities, speech impairments, quality of life	2024	13

4.3 Fluency Disorders (Stuttering)

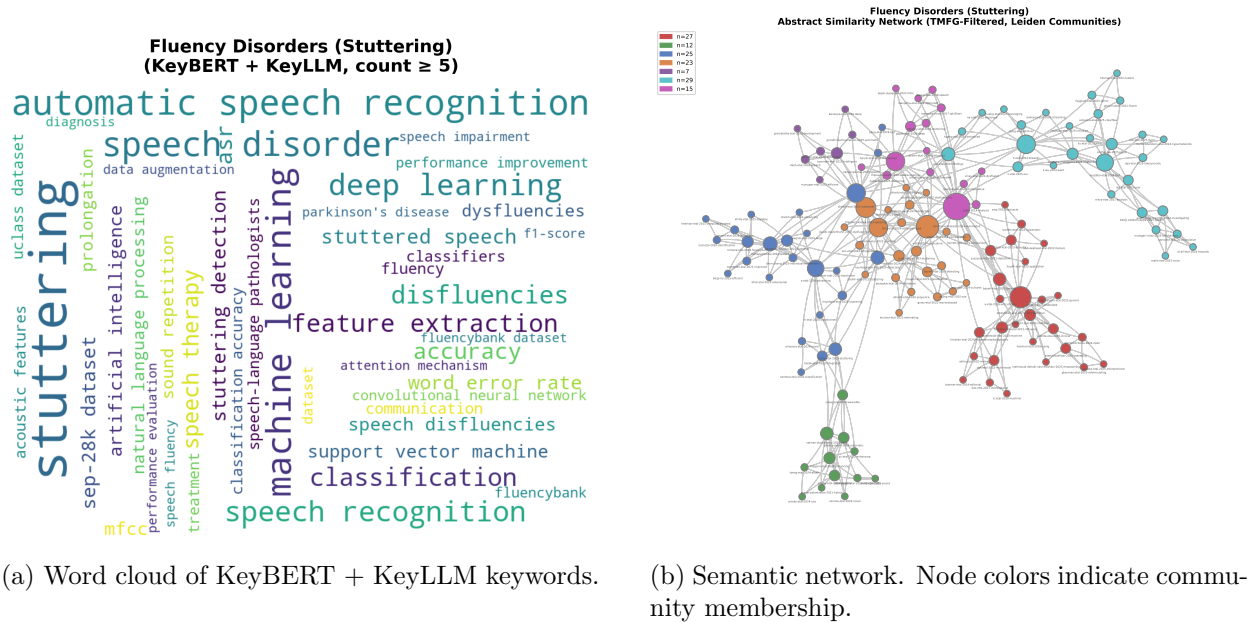


Figure 6: Fluency Disorders (Stuttering): keyword word cloud (a) and abstract similarity network (b).

Table 3: Highest-degree publications per community cluster: Fluency Disorders (Stuttering).

Cluster	Publication	Year	Degree
1	Computational Intelligence-Based Stuttering Detection: A Systematic Review [24]	2023	20

Continued on next page

Continued from previous page

Cluster	Publication	Year	Degree
	<i>Keywords:</i> stuttering, speech disorder, artificial intelligence, computational intelligence, detection, treatment, assessment tools, intervention strategies, personalized approaches, systematic review		
2	Daily Monitoring of Speech Impairment for Early Parkinson's Disease Detection [25] <i>Keywords:</i> chronic neurological diseases, parkinson's disease, pd diagnosis, voice analysis, deep learning, end-to-end model, feature extraction, mfcc, cnn-lstm architecture, accuracy, health monitoring	2023	10
3	StutterNet: Stuttering Detection Using Time Delay Neural Network [26] <i>Keywords:</i> stutternet, stuttering detection, deep learning, disfluencies, automatic speech recognition, asr, time-delay neural network, tdnn, uclass dataset, speakers, acoustic signal, state-of-the-art, residual neural network, parameter sharing	2021	17
4	Evaluative comparison of machine learning algorithms for stutter detection and classification [27] <i>Keywords:</i> stuttering, neuro-developmental speech disorder, speech therapy, speech pathologists, fluency, sep-28k dataset, machine learning models, dysfluency types, acoustic features, class imbalance, speech recognition system, automatic detection, sound repetition, psychological impacts, social interaction, professional advancements	2024	22
5	Intelligent stuttering speech recognition: A succinct review [28] <i>Keywords:</i> stuttering, speech recognition, speech disorder, machine learning, deep learning, classification methods, feature extraction, segmentation, pre-emphasis, speech signal processing, stutter classification	2022	9
6	Towards Fair and Inclusive Speech Recognition for Stuttering: Community-led Chinese Stuttered Speech Dataset Creation and Benchmarking [29] <i>Keywords:</i> automatic speech recognition, asr, stuttering, stuttered speech dataset, mandarin chinese, inclusive speech ai, speech samples, spontaneous conversations, voice command dictations, speech models, biases against disfluent speech, stuttering community, grassroots community	2024	17
7	Automated Dynamic Stuttered Speech Recognition System and Conversion System using Mel Filter And Enhanced Logistic Regression Model [30] <i>Keywords:</i> stuttering, communication, speech recognition, ssr system, fluency, intelligibility, machine learning, sound analysis, prolongation, repetitions, feature extraction, mel frequency cepstral coefficient, disfluencies, interdisciplinary, acoustic data, statistical approaches, deep learning, speech classification, neurodevelopment	2024	26

4.4 Swallowing Disorders (Dysphagia)

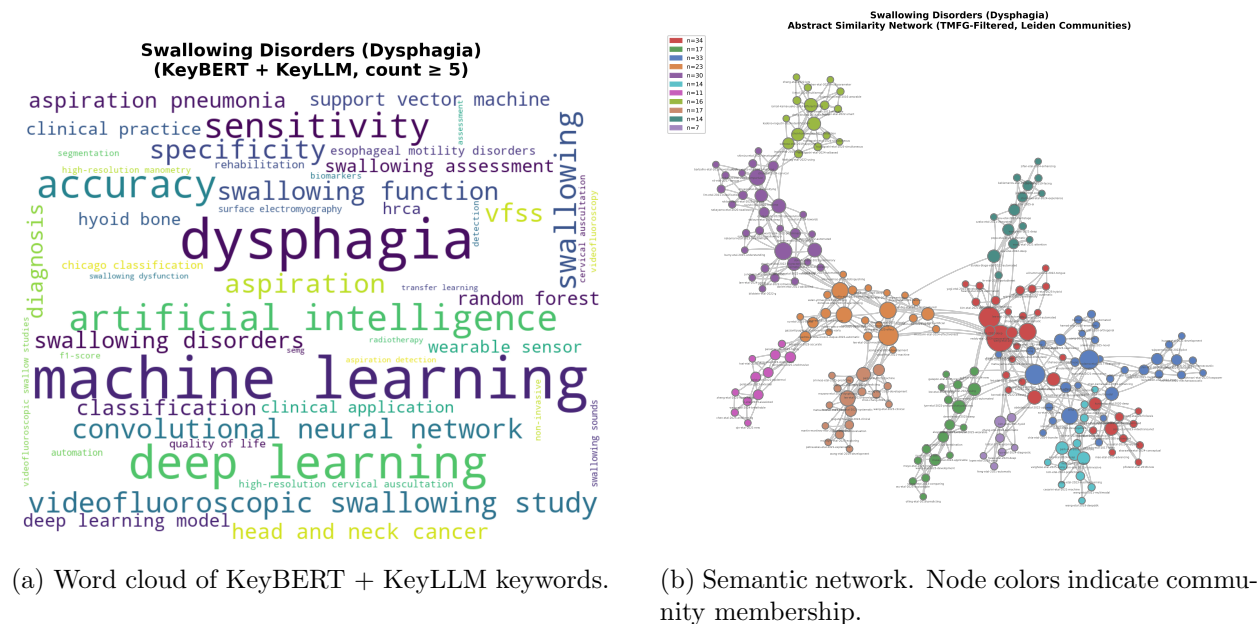


Figure 7: Swallowing Disorders (Dysphagia): keyword word cloud (a) and abstract similarity network (b).

Table 4: Highest-degree publications per community cluster: Swallowing Disorders (Dysphagia).

Cluster	Publication	Year	Degree
1	Deep learning-based video analysis for automatically detecting penetration and aspiration in videofluoroscopic swallowing study [31] <i>Keywords:</i> vfss, dysphagia, deep learning, penetration, aspiration, diagnostic accuracy, convolutional neural network, class imbalance, receiver operating characteristic curve, sensitivity, video review, clinical relevance, multicenter datasets	2025	26
2	Deep learning NTCP model for late dysphagia after radiotherapy for head and neck cancer patients based on 3D dose, CT and segmentations [32] <i>Keywords:</i> deep learning, ntcp model, dysphagia, radiation therapy, 3d dose distribution, organ-at-risk, head and neck cancer, patient toxicity prediction, conventional model, attention maps, swallowing structures, multi-institutional cohort, machine learning, healthcare, predictive modeling	2025	11
3	Autonomous Swallow Segment Extraction Using Deep Learning in Neck-Sensor Vibratory Signals from Patients With Dysphagia [33]	2023	19

Continued on next page

Continued from previous page

Cluster	Publication	Year	Degree
	<i>Keywords:</i> dysphagia, aspiration pneumonia, mortality, instrumental swallowing exams, videofluoroscopic swallowing study, swallowing dysfunction, neck sensors, radiation-free diagnostics, deep convolutional recurrent neural networks, feature extraction, multi-channel swallowing acceleration signals, machine learning, automated annotation, receiver operating characteristic curve, gold standard-labeled segments		
4	The Development of an Artificial Intelligence Video Analysis-Based Web Application to Diagnose Oropharyngeal Dysphagia: A Pilot Study [34] <i>Keywords:</i> dysphagia, videofluoroscopic swallowing study, vfss, artificial intelligence, ai, labeling tool, you only look once, yolov7, dataset, classification, penetration, aspiration, accuracy, dietary options	2024	19
5	Characterizing Effortful Swallows from Healthy Community Dwelling Adults Across the Lifespan Using High-Resolution Cervical Auscultation Signals and MBSImP Scores: A Preliminary Study [35] <i>Keywords:</i> high-resolution cervical auscultation, hrca, dysphagia, swallowing assessment, biofeedback, non-invasive, acoustic signals, vibratory signals, swallowing physiology, machine learning, dysphagia screening, modified barium swallow impairment profile, mbsimp, effortful swallows, non-effortful swallows, vfss, signal processing, diagnostic adjunct, treatment methods, biofeedback system	2022	16
6	Deep learning approach for dysphagia detection by syllable-based speech analysis with daily conversations [36] <i>Keywords:</i> dysphagia, deep learning model, diagnosis, syllable-segmented data, convolutional neural network, audio data, sensitivity, specificity, predictive value, non-invasive, early detection, health complications	2024	10
7	Unobtrusive Swallow Monitoring Enabled by Conformal IONOGEL Biopotential Electrodes and Machine Learning [37] <i>Keywords:</i> dysphagia, difficulty swallowing, electromyography (emg, machine learning, wearable emg system, skin-conformal electrodes, ionic gel electrodes, emg sensing, swallowing events, food types, water volumes, continuous monitoring, personalized healthcare technologies, high accuracy, unobtrusive assessment	2025	8
8	Detection of Fluid Intake Swallowing Events Using Acoustic Signals and Template Matching [38] <i>Keywords:</i> swallowing, physiological process, sound signals, throat microphone, template-matching, acoustic characteristics, classification accuracy, f1-score, non-invasive monitoring, real-time detection, nutrition intake, machine learning, signal stream	2023	11
9	A Systematic and Universal Artificial Intelligence Screening Method for Oropharyngeal Dysphagia: Improving Diagnosis Through Risk Management [39] <i>Keywords:</i> oropharyngeal dysphagia, machine learning, expert system, electronic health records, hospitalized older patients, swallowing assessment, volume-viscosity swallow test, predictive power, feature selection, random forest, area under the roc curve, sensitivity, specificity, positive predictive value, negative predictive value, likelihood ratio, real-time screening, diagnostic strategies, therapeutic strategies	2023	13

Continued on next page

Continued from previous page

Cluster	Publication	Year	Degree
	<i>Keywords:</i> parkinson's disease, pd, dysphonia, machine learning, computer-aided diagnosis, voice disorder measurements, classifiers, svm, linear discriminant analysis, k nearest-neighbors, naïve bayes, regression trees, radial basis function neural networks, performance evaluation, sensitivity, specificity, f-measure, area under the curve, tenfold cross validation, statistical significance		
3	A comparison of cepstral features in the detection of pathological voices by varying the input and filterbank of the cepstrum computation [44] <i>Keywords:</i> automatic voice pathology detection, objective assessment, traditional pipeline approach, deep learning, mel-frequency cepstral coefficient (mfcc, feature extraction, glottal source, vocal tract, quasi-closed phase glottal inverse filtering, filterbank, support vector machine (svm, dysphonia, parkinson's disease, laryngitis, heart failure, detection accuracy, cepstral feature extraction, signal-to-noise ratio (snr	2021	10
4	Voice Pathology Detection Using Convolutional Neural Network and Data Augmentation [45] <i>Keywords:</i> voice disorders, vocal quality, deep learning, convolutional neural network, cnn, data augmentation, mel frequency cepstral coefficients, mfcc, binary classification, normal voices, pathological voices, saarbrücken voice database, svd, accuracy, pathological voice detection, svm, knn techniques	2025	24
5	Hierarchical Multi-Class Classification of Voice Disorders Using Self-Supervised Models and Glottal Features [46] <i>Keywords:</i> automatic classification, voice disorders, binary classification, multi-class classifier, glottal source features, deep learning model, wav2vec 2.0, hubert, hierarchical classifier, mel frequency cepstral coefficients, svm classifiers, classification accuracy, laryngeal disorder, hyperfunctional dysphonia, vocal fold paresis, training data scarcity, feature optimization	2023	39
6	An Analytical Study of Speech Pathology Detection Based on MFCC and Deep Neural Networks [47] <i>Keywords:</i> voice disorders, voice pathology, artificial intelligence, machine learning, voice analysis, automatic speech signal analysis, deep neural network, voice abnormalities, healthcare, saarbruecken voice database, classification, chroma, mel spectrogram, mel frequency cepstral coefficients, accuracy, disease prediction model	2022	35
7	Learning Strategies for Voice Disorder Detection [48] <i>Keywords:</i> voice disorders, health issue, machine learning, acoustic features, voice recordings, deep learning, feature learning, automatic recognition, normal, pathological, datasets, insufficient dataset size, lack of generality	2019	30
8	Exploring Novel Objective Voice Assessment Parameters: A Pilot Study [49] <i>Keywords:</i> objective voice analysis, voice diseases, traditional vocal assessment, cepstrum technology, mel-frequency cepstral coefficient (mfcc, voice characteristics, machine learning algorithms, shapley additive explanations (shap, hoarseness prediction model, voice evaluation indicators	2025	12
9	Deep Learning Application for Vocal Fold Disease Prediction Through Voice Recognition: Preliminary Development Study [50]	2021	24

Continued on next page

Continued from previous page

Cluster	Publication	Year	Degree
10	<p><i>Keywords:</i> dysphonia, vocal fold diseases, pathological voice recognition, artificial intelligence, convolutional neural network, voice disorders, sensitivity, specificity, accuracy, laryngoscopic examination, telemedicine, screening, primary care, mandarin pathological voice database, deep learning</p> <p>Deep learning in automatic detection of dysphonia: Comparing acoustic features and developing a generalizable framework [51]</p> <p><i>Keywords:</i> dysphonia, deep learning, artificial intelligence, auditory-perceptual assessment, acoustic features, convolutional neural network, mel frequency cepstral coefficients, mel-spectrogram, voice quality, classification, vocal health screening, machine learning, clinical evaluation, voice assessment, automatic detection</p>	2023	6

5 Discussion

This study provides a comprehensive, network-based map of AI research across five major areas of communication disorders. By applying keyword extraction and semantic network analysis to over 1,000 publication abstracts, we identified distinct thematic communities within each disorder area and highlighted the most densely connected publications as recommended entry points for clinicians, researchers, and educators seeking to engage with this rapidly growing field. Future work will involve in-depth exploration of each community cluster to characterize its thematic focus, track its evolution over time, and identify specific gaps in clinical implementation and translational research. All bibliographic records and analysis code will be made publicly available upon manuscript submission.

References

- [1] George Vrettas and Mark Sanderson. “Conferences versus journals in computer science.” In: *Journal of the Association for Information Science and Technology* 66.12 (2015), pp. 2674–2684. URL: <https://doi.org/10.1002/asi.23349>.
- [2] Maarten Grootendorst. *KeyBERT: Minimal keyword extraction with BERT*. Version v0.3.0. 2020. URL: <https://doi.org/10.5281/zenodo.4461265>.
- [3] Nils Reimers and Iryna Gurevych. “Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks.” In: *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*. 2019, pp. 3982–3992. URL: <https://aclanthology.org/D19-1410/>.
- [4] Guido Previde Massara, Tiziana Di Matteo, and Tomaso Aste. “Network filtering for big data: Triangulated maximally filtered graph.” In: *Journal of Complex Networks* 5.2 (2016), pp. 161–178.
- [5] Dallin J. Bailey et al. “Generative AI applied to AAC for aphasia: a pilot study of Aphasia-GPT.” eng. In: *Aphasiology* (Jan. 2025), pp. 1–16.
- [6] Charalambos Themistocleous et al. “Part of Speech Production in Patients With Primary Progressive Aphasia: An Analysis Based on Natural Language Processing.” eng. In: *American journal of speech-language pathology* 30.1S (Feb. 2021), pp. 466–480.

- [7] David S. Barbera et al. “NUVA: A Naming Utterance Verifier for Aphasia Treatment.” In: *Computer Speech & Language* 69 (2021), p. 101221. URL: <https://www.sciencedirect.com/science/article/pii/S0885230821000280>.
- [8] Ying Qin et al. “Towards automatic assessment of aphasia speech using automatic speech recognition techniques.” eng. In: *2016 10th International Symposium on Chinese Spoken Language Processing (ISCSLP)*. Oct. 2016, pp. 1–4.
- [9] Sigfus Kristinsson et al. “Machine learning-based multimodal prediction of language outcomes in chronic aphasia.” eng. In: *Human brain mapping* 42.6 (Apr. 2021), pp. 1682–1698.
- [10] Marjory Day et al. “Predicting Severity in People with Aphasia: A Natural Language Processing and Machine Learning Approach.” eng. In: *2021 43rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. Vol. 2021-. Nov. 2021, pp. 2299–2302.
- [11] Kaito Takahashi et al. “Fine-tuning Parakeet-TDT for Dysarthric Speech Recognition in the Speech Accessibility Project Challenge.” In: *Interspeech 2025*. 2025, pp. 3304–3308.
- [12] Yuya Sawa, Ryoichi Takashima, and Tetsuya Takiguchi. “An Investigation of End-to-End Speech Recognition Using Model Adaptation for Dysarthric Speakers.” eng. In: *2020 IEEE 9th Global Conference on Consumer Electronics (GCCE)*. Oct. 2020, pp. 480–481.
- [13] S Keerthika et al. “Enhancing Dysarthria Diagnosis With Deep Learning Techniques.” eng. In: *International Conference on Computing, Communication, and Networking Technologies (Online)*. June 2024, pp. 1–6.
- [14] Zhaopeng Qian and Kejing Xiao. “A Survey of Automatic Speech Recognition for Dysarthric Speech.” eng. In: *Electronics (Basel)* 12.20 (Oct. 2023), pp. 4278–.
- [15] Myungjong Kim, Jun Wang, and Hoirin Kim. “Dysarthric Speech Recognition Using Kullback-Leibler Divergence-Based Hidden Markov Model.” In: *Interspeech 2016*. 2016, pp. 2671–2675.
- [16] Seyed Reza Shahamiri, Krishnendu Mandal, and Sudeshna Sarkar. “Dysarthric Speech Recognition using Depthwise Separable Convolutions: Preliminary Study.” eng. In: *International Conference on Speech Technology and Human-Computer Dialogue (Online)*. Oct. 2023, pp. 78–82.
- [17] Ming Tu et al. “The relationship between perceptual disturbances in dysarthric speech and automatic speech recognition performance.” eng. In: *The Journal of the Acoustical Society of America* 140.5 (Nov. 2016), EL416–EL422.
- [18] Medha Malik and Ruqaiya Khanam. “Efficacy of Current Dysarthric Speech Recognition Techniques.” eng. In: *2023 International Conference on Advanced Computing & Communication Technologies (ICACCTech)*. Dec. 2023, pp. 657–663.
- [19] Mengzhe Geng et al. “Homogeneous Speaker Features for on-the-Fly Dysarthric and Elderly Speaker Adaptation and Speech Recognition.” eng. In: *IEEE Transactions on Audio, Speech and Language Processing* 33 (2025), pp. 1689–1705.
- [20] Brahim Fares Zaidi et al. “Deep neural network architectures for dysarthric speech analysis and recognition.” eng. In: *Neural computing & applications* 33.15 (Aug. 2021), pp. 9089–9108.
- [21] Kyle Hall, Andy Huang, and Seyed Reza Shahamiri. “An Investigation to Identify Optimal Setup for Automated Assessment of Dysarthric Intelligibility using Deep Learning Technologies.” eng. In: *Cognitive computation* 15.1 (Jan. 2023), pp. 146–158.

- [22] Chen Zhang, Chen Gong, and Yanan Sui. “Dysarthria Detection with Deep Representation Learning for Patients with Parkinson’s Disease.” eng. In: *2024 46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. Vol. 2024. July 2024, pp. 1–5.
- [23] Goldy Verma et al. “Next-Gen Speech Disorder Diagnostics: CNN Methods for Dysarthria Classification.” eng. In: *2024 First International Conference on Pioneering Developments in Computer Science & Digital Technologies (IC2SDT)*. Aug. 2024, pp. 365–369.
- [24] Raghad Alnashwan et al. “Computational Intelligence-Based Stuttering Detection: A Systematic Review.” eng. In: *Diagnostics (Basel)* 13.23 (Nov. 2023), pp. 3537–.
- [25] Al Jizani Mohammed Kadhim Salman and Grigore Stamatescu. “Daily Monitoring of Speech Impairment for Early Parkinson’s Disease Detection.” eng. In: *Proceedings of the ... IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems (Online)*. Vol. 1. Sept. 2023, pp. 1049–1053.
- [26] Shakeel A Sheikh et al. “StutterNet: Stuttering Detection Using Time Delay Neural Network.” eng. In: *2021 29th European Signal Processing Conference (EUSIPCO)* (June 2021), pp. 426–430.
- [27] Ramitha V et al. “Evaluative comparison of machine learning algorithms for stutter detection and classification.” eng. In: *MethodsX* 13 (Dec. 2024), pp. 103050–.
- [28] Nilanjan Banerjee, Samarjeet Borah, and Nilambar Sethi. “Intelligent stuttering speech recognition: A succinct review.” eng. In: *Multimedia tools and applications* 81.17 (July 2022), pp. 24145–24166.
- [29] Qisheng Li et al. “Towards Fair and Inclusive Speech Recognition for Stuttering: Community-led Chinese Stuttered Speech Dataset Creation and Benchmarking.” eng. In: *CHI 2024 - Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems*. May 2024, pp. 1–9.
- [30] K. Niroscha and N. Venkatesh. “Automated Dynamic Stuttered Speech Recognition System and Conversion System using Mel Filter And Enhanced Logistic Regression Model.” eng. In: *2024 3rd International Conference on Automation, Computing and Renewable Systems (ICACRS)*. Dec. 2024, pp. 1254–1261.
- [31] Soyoung Kwak et al. “Deep learning-based video analysis for automatically detecting penetration and aspiration in videofluoroscopic swallowing study.” eng. In: *Scientific reports* 15.1 (July 2025), pp. 24296–8.
- [32] S.P.M. de Vette et al. “Deep learning NTCP model for late dysphagia after radiotherapy for head and neck cancer patients based on 3D dose, CT and segmentations.” eng. In: *Radiotherapy and oncology* 213 (Dec. 2025), pp. 111169–111169.
- [33] Yassin Khalifa et al. “Autonomous Swallow Segment Extraction Using Deep Learning in Neck-Sensor Vibratory Signals from Patients With Dysphagia.” eng. In: *IEEE journal of biomedical and health informatics* 27.2 (Feb. 2023), pp. 1–13.
- [34] Chang-Won Jeong et al. “The Development of an Artificial Intelligence Video Analysis-Based Web Application to Diagnose Oropharyngeal Dysphagia: A Pilot Study.” eng. In: *Brain sciences* 14.6 (June 2024), pp. 546–.
- [35] Cara Donohue et al. “Characterizing Effortful Swallows from Healthy Community Dwelling Adults Across the Lifespan Using High-Resolution Cervical Auscultation Signals and MB-SImP Scores: A Preliminary Study.” eng. In: *Dysphagia* 37.5 (Oct. 2022), pp. 1103–1111.

- [36] Seokhyeon Heo et al. “Deep learning approach for dysphagia detection by syllable-based speech analysis with daily conversations.” eng. In: *Scientific reports* 14.1 (Aug. 2024), pp. 20270–9.
- [37] Penghao Dong et al. “Unobtrusive Swallow Monitoring Enabled by Conformal IONOGEL Biopotential Electrodes and Machine Learning.” eng. In: *Advanced materials technologies* 10.16 (Aug. 2025).
- [38] Xin Chen and Ernest Kamavuako. “Detection of Fluid Intake Swallowing Events Using Acoustic Signals and Template Matching.” eng. In: *Proceedings / Annual IEEE International Symposium on Bioinformatics and Bioengineering (BIBE)*. Dec. 2023, pp. 403–408.
- [39] Alberto Martin-Martinez et al. “A Systematic and Universal Artificial Intelligence Screening Method for Oropharyngeal Dysphagia: Improving Diagnosis Through Risk Management.” eng. In: *Dysphagia* 38.4 (Aug. 2023), pp. 1224–1237.
- [40] Teodora Surdea-Blaga et al. “Automated Chicago Classification for Esophageal Motility Disorder Diagnosis Using Machine Learning.” eng. In: *Sensors (Basel, Switzerland)* 22.14 (July 2022), pp. 5227–.
- [41] Zhenwei Zhang, James L. Coyle, and Ervin Sejdić. “Automatic hyoid bone detection in fluoroscopic images using deep learning.” eng. In: *Scientific reports* 8.1 (Aug. 2018), pp. 12310–9.
- [42] Sidra Abid Syed et al. “Inter classifier comparison to detect voice pathologies.” eng. In: *Mathematical biosciences and engineering : MBE* 18.3 (Mar. 2021), pp. 2258–2273.
- [43] Salim Lahmiri, Debra Ann Dawson, and Amir Shmuel. “Performance of machine learning methods in diagnosing Parkinson’s disease based on dysphonia measures.” eng. In: *Biomedical engineering letters* 8.1 (Feb. 2018), pp. 29–39.
- [44] Mittapalle Kiran Reddy and Paavo Alku. “A comparison of cepstral features in the detection of pathological voices by varying the input and filterbank of the cepstrum computation.” eng. In: *IEEE access* 9 (Jan. 2021), pp. 1–1.
- [45] Ibrahim Missaoui, Walid Toumi, and Zied Lachiri. “Voice Pathology Detection Using Convolutional Neural Network and Data Augmentation.” eng. In: *2025 IEEE International Conference on Advanced Systems and Emergent Technologies (IC_ASET)*. May 2025, pp. 1–5.
- [46] Saska Tirronen, Sudarsana Reddy Kadiri, and Paavo Alku. “Hierarchical Multi-Class Classification of Voice Disorders Using Self-Supervised Models and Glottal Features.” eng. In: *IEEE open journal of signal processing* 4 (2023), pp. 80–88.
- [47] Mohammed Zakariah et al. “An Analytical Study of Speech Pathology Detection Based on MFCC and Deep Neural Networks.” eng. In: *Computational and mathematical methods in medicine* 2022 (Apr. 2022), pp. 1–15.
- [48] Hongzhao Guan and Alexander Lerch. “Learning Strategies for Voice Disorder Detection.” eng. In: *2019 IEEE 13th International Conference on Semantic Computing (ICSC)*. Jan. 2019, pp. 295–301.
- [49] Zufe Li et al. “Exploring Novel Objective Voice Assessment Parameters: A Pilot Study.” eng. In: *Journal of voice* (June 2025).
- [50] Hao-Chun Hu et al. “Deep Learning Application for Vocal Fold Disease Prediction Through Voice Recognition: Preliminary Development Study.” eng. In: *Journal of medical Internet research* 23.6 (June 2021), e25247–.

- [51] Zhen Chen et al. “Deep learning in automatic detection of dysphonia: Comparing acoustic features and developing a generalizable framework.” eng. In: *International journal of language & communication disorders* 58.2 (Mar. 2023), pp. 279–294.