

Transforming Research Methodology in Audiology and Speech-Language Pathology: Emerging Paradigms, Technological Innovation, and Methodological Excellence

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Abstract

Audiology and Speech-Language Pathology (ASLP) research is undergoing substantial methodological transformation through artificial intelligence (AI), machine learning (ML), telepractice, mixed methods, multimodal data, longitudinal assessment, and interoperable data systems. This critical narrative review with structured evidence mapping examined emerging methodological paradigms and their implications for validity, reliability, external validation, reproducibility, data standardisation, cultural and linguistic responsiveness, and clinical translation. The primary evidence window covered January 2015 to August 2026, with earlier foundational methodological sources retained where relevant. Fifty-two core documents were included in the analytical corpus. Recent evidence demonstrates rapid technological expansion: Frosolini et al. (2024) identified 1,359 records and included 104 manuscripts in an AI-audiology scoping review, with 87.5% published during the preceding four years. Scott et al. (2025) identified nine randomised controlled trials comparing telehealth with face-to-face speech-language pathology, while Vercammen et al. (2026) reported data-standardisation findings from 82 survey participants and five experts, with 90% of respondents willing to follow or contribute to standardisation efforts. Across the literature, technological development has progressed faster than methodological harmonisation, particularly in external validation, measurement standardisation, interoperability, representation, reproducibility, and implementation. An integrated framework is therefore proposed linking the research question, design, measurement, technology, analysis, validation, contextual responsiveness, implementation, and clinical meaning. Methodological excellence in ASLP should ultimately be defined by rigorous, transparent, reproducible, equitable, and clinically meaningful evidence rather than technological novelty alone.

Keywords: Audiology, speech-language pathology, research methodology, artificial intelligence, evidence-based practice

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1. Introduction

Audiology and Speech-Language Pathology comprise clinically complex disciplines in which phenomena are shaped by interactions among biological, perceptual, cognitive, linguistic, behavioural, social, cultural, and environmental factors. Research consequently

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needs to answer questions that extend beyond whether a test, intervention, technology, or service is effective under controlled conditions. High-quality evidence must also address whom an intervention benefits, in which contexts, through which mechanisms, at what cost, with what adverse consequences, and whether measured change is meaningful to patients and communication partners. The methodological challenge is therefore one of evidence generation that is simultaneously rigorous, interpretable, reproducible, and clinically relevant.

Evidence-based Practice (EBP) remains a foundational principle in this process. The classical formulation of evidence-based medicine emphasised the integration of the best available external evidence with clinical expertise and individual preferences (Sackett et al., 1996). In ASLP, however, the evidence base is methodologically diverse. Randomised trials, observational studies, psychometric investigations, qualitative studies, single-case experimental designs, diagnostic accuracy research, evidence syntheses, implementation studies, and mixed-methods designs address different aspects of clinical uncertainty. Methodological pluralism is therefore necessary, but pluralism without coordination can generate substantial heterogeneity in constructs, measures, analytical procedures, reporting standards, and data structures (Greenwell & Walsh, 2021; Hryciw et al., 2026).

At the same time, ASLP research is being reshaped by technological change. AI and ML are increasingly applied to audiological screening, automated assessment, signal processing, diagnosis, classification, prediction, speech analysis, and personalised intervention (Frosolini et al., 2024; Cordella et al., 2025; Koçak, 2026). Frosolini et al. (2024) identified 1,359 records in a scoping review of AI in audiology and included 104 manuscripts, with 87.5% of the included manuscripts published during the four years immediately preceding the review. The magnitude and temporal concentration of this evidence indicate a rapidly expanding field rather than a mature methodological tradition.

The same expansion is apparent in speech and language research. Tbaishat et al. (2025) identified 70 studies in a systematic mapping study of AI for the diagnosis of speech and language disorders, while Brahmi et al. (2024) synthesised 65 studies addressing ML-based approaches to speech disorders. Cordella et al. (2025) further described an expanding range of ML applications relevant to speech-language pathology, while emphasising the importance of understanding dataset characteristics, model development, validation, interpretability, and limitations.

Telepractice represents another major methodological transition. Its development has created questions concerning access, clinical equivalence, treatment fidelity, patient engagement, and the influence of environmental context. Importantly, the literature has progressed from predominantly feasibility-oriented reports towards controlled comparative research. Scott et al. (2025) identified nine randomised controlled trials comparing live telehealth with face-to-face speech-language pathology services. Eight trials used video and one used telephone delivery. The review found no statistically significant differences for several principal outcomes but also identified important gaps in quality-of-life, satisfaction, well-being, and economic evidence.

Research data themselves are also becoming a methodological issue. Contemporary ASLP studies increasingly generate longitudinal, multimodal, machine-readable data that may combine auditory measures, acoustic and linguistic features, behavioural outcomes, patient-reported measures, imaging, clinical metadata, and contextual variables. Without shared definitions, metadata, provenance, and interoperable structures, such data cannot be readily combined or reused. Wilkinson et al. (2016) established the broader FAIR principles for making data findable, accessible, interoperable, and reusable, while subsequent work has emphasised transparent dataset documentation and model reporting (Gebru et al., 2021; Mitchell et al., 2019).

The need for standardisation is now being recognised explicitly within audiology. Vercammen et al. (2026) reported a mixed-methods investigation involving 82 members of the global computational audiology community and five experts. Ninety percent of survey respondents reported willingness to follow or contribute to standardisation efforts, while the expert panel identified harmonisation challenges and possible alignment with broader health-data standards. Such evidence suggests that standardisation is becoming a social, technical, and governance issue rather than simply a matter of database design.

Methodological excellence must also encompass representation. Cultural and linguistic diversity directly affects measurement, interpretation, and generalisability in ASLP. Evidence concerning culturally and linguistically diverse populations continues to identify limitations in assessment tools, training, professional representation, and service provision (Medina et al., 2022; Sinclair et al., 2025). Bampoe et al. (2025), for example, highlighted the need for assessment resources that are explicitly responsive to Ghanaian English rather than simply importing instruments developed in other linguistic contexts.

These changes collectively raise a central methodological question: how can ASLP research integrate technological innovation without weakening measurement quality, transparency, external validity, reproducibility, cultural responsiveness, or clinical meaning? The purpose of this review is to address that question by examining emerging methodological paradigms, synthesising their strengths and limitations, and proposing an integrated framework for methodological excellence.

2. Literature Review

2.1 Evidence-Based Practice and Evidence Synthesis

EBP provides a conceptual foundation for contemporary ASLP research because it places research evidence within a broader decision-making process rather than treating statistical findings as self-sufficient. In speech-language pathology, exposure to EBP and research methodology has been linked with clinical use of evidence, while practical constraints such as time, workload, and access to research remain important barriers (Greenwell & Walsh, 2021).

Evidence synthesis has consequently diversified. Systematic reviews remain appropriate for focused questions with relatively coherent evidence, whereas scoping reviews can map broader or emerging literatures and accommodate methodological heterogeneity (Peters et al., 2020; Tricco et al., 2018). The methodological implication is that the form

of synthesis should be driven by the question and evidence structure. Overuse of one synthesis design can itself become a source of methodological distortion.

Whitehorn et al. (2020) further demonstrated the importance of methodological transparency in evidence summaries. The quality of a synthesis depends not only on its conclusions but also on how evidence is selected, appraised, summarised, and communicated. This principle is directly relevant to rapidly developing AI and digital-health literatures in which evidence quality can vary markedly within the same broad technological domain.

2.2 Methodological Pluralism and Mixed Methods

ASLP research frequently involves both empirical and experiential questions. Quantitative methods estimate effects, diagnostic accuracy, associations, and predictive performance; qualitative approaches address experience, meaning, acceptability, context, and implementation. Mixed methods can integrate these forms of evidence when integration is explicitly designed rather than occurring only at the reporting stage (Creswell & Plano Clark, 2018).

Hryciw et al. (2026) emphasised that mixed-methods research can support evidence-based speech-language pathology by combining quantitative and qualitative information to produce findings that are responsive to person-centred and sociocultural contexts. Qualitative methodological rigour also requires attention to context, coherence, transparency, and practical importance (Yardley, 2000). Braun and Clarke (2006) further established thematic analysis as a flexible but systematic approach to identifying and interpreting patterns in qualitative data.

Methodological pluralism is especially valuable for technology research. For example, a study of AI-supported assessment may quantify diagnostic discrimination while simultaneously exploring clinician trust, patient acceptability, interpretability, and workflow integration. Such questions cannot be answered adequately through predictive performance metrics alone.

2.3 Measurement Science and Outcome Standardisation

Measurement is the foundation on which all subsequent inference depends. Validity concerns the defensibility of interpreting scores for their intended purpose (Messick, 1995; Cook & Beckman, 2006), whereas reliability concerns the consistency of measurement under specified conditions. Agreement between measurements also requires appropriate methods; correlation alone does not establish interchangeability (Bland & Altman, 1986).

Modern psychometric standards emphasise systematic evaluation of reliability, validity, responsiveness, and interpretability (Mokkink et al., 2010; Terwee et al., 2007). The intraclass correlation coefficient, for example, has multiple forms with different assumptions, and researchers should specify the model used and its rationale rather than reporting ICC values without adequate detail (Koo & Li, 2016).

Measurement heterogeneity is a persistent issue in ASLP. Denman et al. (2017) identified

considerable variability in the psychometric evidence supporting language assessments for children. In aphasia, Stark et al. (2021a) reported heterogeneity in discourse measures, methods, and analyses sufficient to constrain cross-study comparison and replication. Stark et al. (2021b) subsequently demonstrated substantial international variation in spoken discourse assessment and analysis practice.

The development of automated and AI-derived measures does not remove this problem. It may intensify it if researchers focus on computational precision without first establishing what construct the algorithm is intended to measure. Methodological innovation therefore needs to proceed from measurement validity towards automation, not from automation towards retrospective justification.

2.4 Artificial Intelligence and Machine Learning

AI and ML are increasingly prominent within ASLP research. In audiology, applications extend across diagnostic classification, automated assessment, signal processing, rehabilitation, hearing-device optimisation, and digital health (Frosolini et al., 2024; Koçak, 2026). In speech and language research, ML has been applied to dysarthria, aphasia, speech recognition, voice disorders, and other communication disorders (Brahmi et al., 2024; Cordella et al., 2025; Tbaishat et al., 2025).

Modern AI methods require researchers to consider issues beyond algorithm selection. Dataset provenance, sampling, class imbalance, missing data, feature construction, data leakage, hyperparameter tuning, internal and external validation, calibration, uncertainty, interpretability, and intended use all affect the credibility of computational findings (Wiens et al., 2019; Collins et al., 2024). Broader medical AI literature has also demonstrated that algorithmic performance can vary across demographic groups when training data and outcome definitions are not appropriately aligned (Obermeyer et al., 2019).

The methodological literature therefore increasingly distinguishes technical performance from clinical utility. Topol (2019) and Esteva et al. (2019) described the transformative potential of AI while recognising limitations related to bias, transparency, generalisability, and integration. The World Health Organization (2021) similarly emphasised ethical governance, accountability, inclusiveness, and human oversight.

2.5 Multimodal and Longitudinal Research

Multimodal research can combine auditory, acoustic, linguistic, behavioural, neuroimaging, functional, and patient-reported data. Longitudinal designs add information about individual trajectories, adaptation, treatment response, and delayed effects. Together, these approaches can produce more realistic models of communication and hearing outcomes than single time-point measures.

Their methodological demands are correspondingly greater. Repeated observations cannot be treated as independent merely because more measurements are collected. Researchers need explicit approaches to dependency structures, missing data, time-varying confounding, measurement drift, and analytic reproducibility. Increased data volume should therefore be distinguished from increased evidential strength.

2.6 Telepractice and Digital Health

Telepractice has become a major methodological domain in ASLP. The contemporary literature increasingly evaluates telehealth through controlled comparisons rather than only feasibility and satisfaction studies. Scott et al. (2025) identified nine randomised controlled trials, with eight using video and one using telephone delivery. Trials involved stuttering, Parkinson's disease, post-stroke conditions, speech sound disorders, and voice disorders. For the principal stuttering outcome, percentage syllables stuttered, the meta-analysis found no significant difference between telehealth and face-to-face delivery across examined follow-up points; similar absence of significant differences was reported for the Parkinson's disease outcome of change in monologue sound pressure levels. The evidence base nevertheless remained small and did not adequately cover several patient-centred and economic outcomes.

The wider evidence also indicates that telepractice encompasses more than direct patient treatment. Walters et al. (2025) reviewed telesupervision for speech-language pathology students and found eight studies addressing its use, with its implementation influenced by technology access and training, caseload, educator characteristics, and the supervisory relationship. Palomares-Aguilera et al. (2021) demonstrated the feasibility of telepractice in a specialised paediatric context, while Varma et al. (2025) synthesised evidence on teletherapy for voice disorders.

These findings suggest that the relevant methodological question is not simply whether telepractice is equivalent to face-to-face care. Researchers need to determine when, for whom, for which intervention, and under what technological and contextual conditions remote delivery produces clinically meaningful outcomes.

2.7 Data Standardisation and Interoperability

Data standardisation is increasingly central to ASLP research because computational methods depend on datasets that can be combined, interpreted, and reused. The FAIR principles provide a broader infrastructure framework for improving data reuse (Wilkinson et al., 2016). Dataset documentation approaches such as datasheets and model cards further emphasise transparency about data provenance, intended use, subgroup performance, and limitations (Geburu et al., 2021; Mitchell et al., 2019).

Vercammen et al. (2026) provide particularly direct evidence for audiology. Their survey included 82 members of the global computational audiology community and their expert panel included five experts. Ninety percent of survey participants indicated willingness to follow or contribute to standardisation efforts. The study also identified harmonisation as a key challenge and considered interoperability with standards such as OMOP, openEHR, and Noah.

Standardisation should therefore include variable definitions, data dictionaries, metadata, ontologies, coding schemes, provenance, quality checks, versioning, and governance. It should also be treated as a maintained infrastructure rather than a one-time project.

2.8 Cultural and Linguistic Responsiveness

The validity of an ASLP measure depends on the population in which it is used.

Linguistic structure, dialect, accent, cultural practices, communication norms, educational background, and clinical context can all influence test performance and interpretation. Medina et al. (2022) examined barriers affecting culturally and linguistically diverse individuals within speech-language pathology training and professional pathways, while Sinclair et al. (2025) identified recurring issues in SLP experiences with culturally and linguistically diverse families.

Bampoe et al. (2025) provide a particularly relevant example through development of a Ghanaian-English speech and language assessment tool. Their work demonstrates that culturally and linguistically responsive methodology requires active engagement with the target community rather than simple translation of existing measures.

These issues become especially consequential in AI. A computational model trained primarily on one linguistic population may reproduce or magnify inequities when applied elsewhere. Cultural and linguistic responsiveness should therefore be considered a property of the entire methodological pipeline, including sampling, annotation, measurement, training, validation, and implementation.

2.9 Reproducibility, Reporting, and Implementation

Transparent reporting is essential for converting individual studies into cumulative science. CONSORT 2010 provides core guidance for randomised controlled trials (Schulz et al., 2010), STROBE for observational studies (von Elm et al., 2007), COREQ and SRQR for qualitative work (Tong et al., 2007; O'Brien et al., 2014), and PRISMA-ScR for scoping reviews (Tricco et al., 2018). AI-enabled research has prompted additional reporting standards, including SPIRIT-AI, CONSORT-AI, and TRIPOD+AI (Rivera et al., 2020; Liu et al., 2020; Collins et al., 2024).

Reproducibility is not limited to reporting methods. It also depends on accessible data structures, documented analysis code, transparent preprocessing, stable software environments, and clear model specifications. Heinrich and Knight (2020) highlighted reproducibility as an important concern in cognitive hearing research, while responsible ML frameworks emphasise the need to address translation from development to real-world deployment (Wiens et al., 2019).

Implementation science provides the final methodological bridge. Proctor et al. (2011) distinguished implementation outcomes such as acceptability, adoption, appropriateness, feasibility, fidelity, cost, penetration, and sustainability from conventional clinical outcomes. Greenhalgh et al. (2017) similarly demonstrated that technology adoption depends on multiple interacting conditions rather than technological performance alone. The updated Consolidated Framework for Implementation Research further incorporates the role of contextual determinants and equity in implementation (Damschroder et al., 2022).

3. Research Gap

The evidence demonstrates substantial methodological innovation but also considerable fragmentation. First, technological development, particularly AI and ML, is proceeding

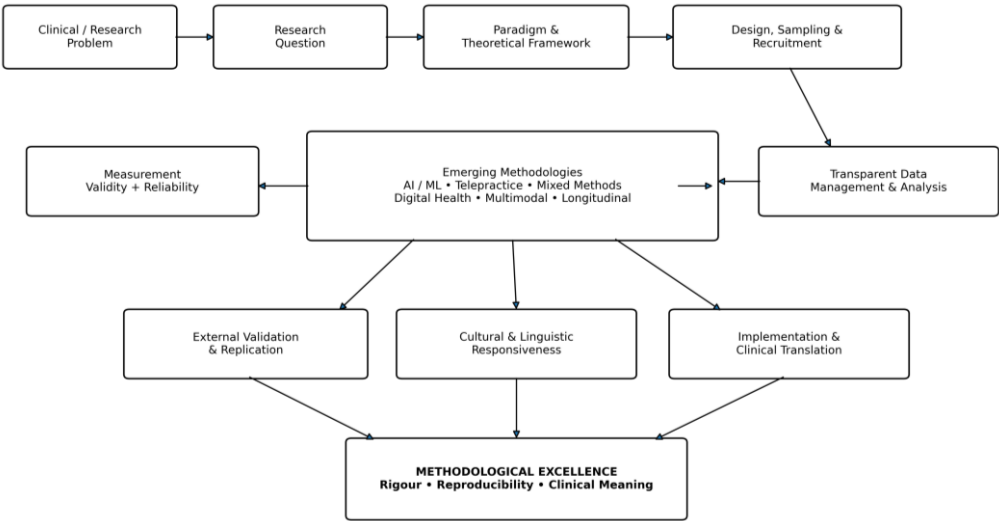
faster than consensus concerning benchmark datasets, outcome definitions, external validation, subgroup evaluation, and clinical utility. Second, measurement heterogeneity remains a persistent limitation across speech, language, discourse, voice, and hearing outcomes. Third, many computational studies remain focused on proof-of-concept or internal validation, restricting generalisability to other populations and clinical settings.

Fourth, data infrastructures are not yet sufficiently harmonised for large-scale collaborative research. Interoperability requires common terminology, metadata, provenance, governance, and sustainable stewardship. Fifth, cultural and linguistic diversity remains inadequately represented in many assessment systems and computational datasets. Sixth, methodological education has not fully kept pace with the emerging requirements of AI-enabled research. Brock (2026) identified 25 papers and 11 instructional approaches for teaching EBP to speech-language pathology students but found that much of the literature relied on self-report rather than objective measures of learning outcomes.

A further gap exists in implementation. Strong statistical or predictive performance does not guarantee clinical adoption, sustainability, safety, equity, or patient benefit. ASLP research therefore needs an integrated model that connects research questions, design, measurement, data governance, computational methods, validation, contextual responsiveness, and implementation. The integrated methodological framework developed from these gaps is presented in Figure 1.

Figure 1

Integrated methodological framework for methodological excellence in ASLP research



The framework links the clinical or research problem to the research question, paradigm, design, measurement, emerging methodology, data management, validation, cultural and linguistic responsiveness, implementation, and clinical meaning.

4. Objectives

- a. To examine emerging methodological paradigms transforming Audiology and Speech-Language Pathology, particularly AI and ML, telepractice, mixed methods, multimodal research, longitudinal designs, and data standardisation.
- b. To synthesise published evidence concerning the strengths and limitations of these paradigms in relation to measurement quality, validity, reliability, external validation, reproducibility, interoperability, cultural and linguistic responsiveness, and implementation.
- c. To develop an integrated framework linking research design, measurement, technology, analysis, validation, implementation, and clinical relevance as components of methodological excellence.

5. Methodology

5.1 Study Design

A critical narrative review with structured evidence mapping was conducted. This design was selected because the review sought to integrate conceptually and methodologically heterogeneous evidence rather than estimate a single pooled intervention effect. The approach permitted synthesis across empirical studies, systematic and scoping reviews, methodological frameworks, reporting standards, implementation models, and technology-focused research.

5.2 Timeframe and Rationale

The primary evidence window extended from 1 January 2015 to 31 August 2026. This interval was selected to capture the contemporary expansion of AI, ML, telepractice, digital health, data-intensive research, interoperability, and implementation science in ASLP. Earlier sources were retained selectively when they represented foundational methodological standards that continue to underpin contemporary research, including validity, psychometrics, qualitative quality, EBP, implementation, reporting, and evidence synthesis. The final analytical corpus comprised 52 core documents. This number refers to the sources used for detailed synthesis and should not be interpreted as an exhaustive database retrieval or systematic-review screening count.

5.3 Information Sources

Evidence was identified from PubMed/MEDLINE, Scopus, Web of Science, Google Scholar, Cochrane resources, ScienceDirect, relevant publisher platforms, Wiley Online Library, reference lists of key articles, and authoritative methodological and reporting-guideline sources. Particular emphasis was placed on peer-reviewed systematic reviews, scoping reviews, methodological studies, empirical comparative research, consensus guidelines, and established research frameworks. Recent publications were checked against journal or PubMed records when bibliographic details or publication status required confirmation.

5.4 Search Strategy

The search strategy combined concept groups for ASLP, research methodology, technological innovation, and methodological quality using the Boolean operators AND and OR. A representative strategy was: (audiology OR "speech-language pathology" OR "speech language pathology" OR "communication disorders") AND ("research methodology" OR "research design" OR "mixed methods" OR "evidence-based practice") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR telepractice OR telehealth OR "digital health" OR multimodal OR longitudinal OR interoperability OR "data standardisation"). Additional targeted searches were undertaken for psychometric validity and reliability, AI and ML, external validation, reproducibility, cultural and linguistic responsiveness, data standardisation, implementation science, and technology-specific reporting standards.

5.5 Inclusion Criteria

Documents were included when they made a substantive contribution to ASLP research methodology, measurement, evidence synthesis, AI or ML, telepractice, digital health, multimodal research, longitudinal design, data standardisation, reproducibility, cultural and linguistic responsiveness, research education, or implementation. Peer-reviewed empirical studies, systematic reviews, scoping reviews, methodological articles, reporting standards, consensus documents, and foundational methodological books were eligible. Relevant methodological evidence from wider health research was retained when it had direct applicability to ASLP.

5.6 Exclusion Criteria

Documents were excluded when they were unrelated to ASLP or transferable health-research methodology, lacked a methodological contribution, were primarily promotional or commercial, duplicated another source without additional methodological value, or described technical development without meaningful implications for measurement, validity, clinical interpretation, transparency, implementation, or research quality.

5.7 Data Standardisation

Data were extracted into a structured evidence matrix. The extracted variables included publication year, discipline, study type, methodological paradigm, technology or research approach, population or evidence context, principal outcome or methodological variable, validation approach, key methodological strength, principal limitation, and implications for ASLP research. Quantitative values reported by source studies were retained as published. Where sources used conceptually similar terms with different labels, terminology was harmonised during synthesis while preserving the original construct meaning. Particular attention was given to distinguishing records identified from manuscripts included, sample size from number of studies, technical performance from clinical utility, internal from external validation, and reported percentages from percentages calculated by mathematical complement. This process reduced the risk of conflating measures that appeared superficially similar but represented different methodological quantities.

5.8 Evidence-Mapping and Synthesis

Evidence was organised into nine domains: EBP and evidence synthesis; methodological pluralism and mixed methods; measurement and psychometrics; AI and ML; multimodal and longitudinal research; telepractice and digital health; data standardisation and interoperability; cultural and linguistic responsiveness; and reproducibility, reporting, and implementation. Braun and Clarke's (2006) principles of systematic thematic analysis informed the identification of recurring methodological patterns, while the qualitative quality principles described by Yardley (2000) informed interpretation of contextual and experiential evidence. Quantitative data were summarised descriptively rather than re-analysed across studies with incompatible denominators or designs.

5.9 Methodological and Reporting Frameworks

Interpretation was informed by established reporting and methodological standards, including CONSORT 2010, STROBE, COREQ, SRQR, PRISMA-ScR, SPIRIT-AI, CONSORT-AI, TRIPOD+AI, and COSMIN-related measurement principles (Schulz et al., 2010; von Elm et al., 2007; Tong et al., 2007; O'Brien et al., 2014; Tricco et al., 2018; Rivera et al., 2020; Liu et al., 2020; Collins et al., 2024; Mookink et al., 2010).

5.10 Ethical Considerations

The study used previously published literature and did not involve recruitment of human participants or collection of identifiable primary data. Institutional ethical approval was therefore not required. The synthesis nevertheless adhered to principles of accurate attribution, preservation of original meanings, transparent reporting of quantitative evidence, and explicit separation between published findings and methodological interpretation.

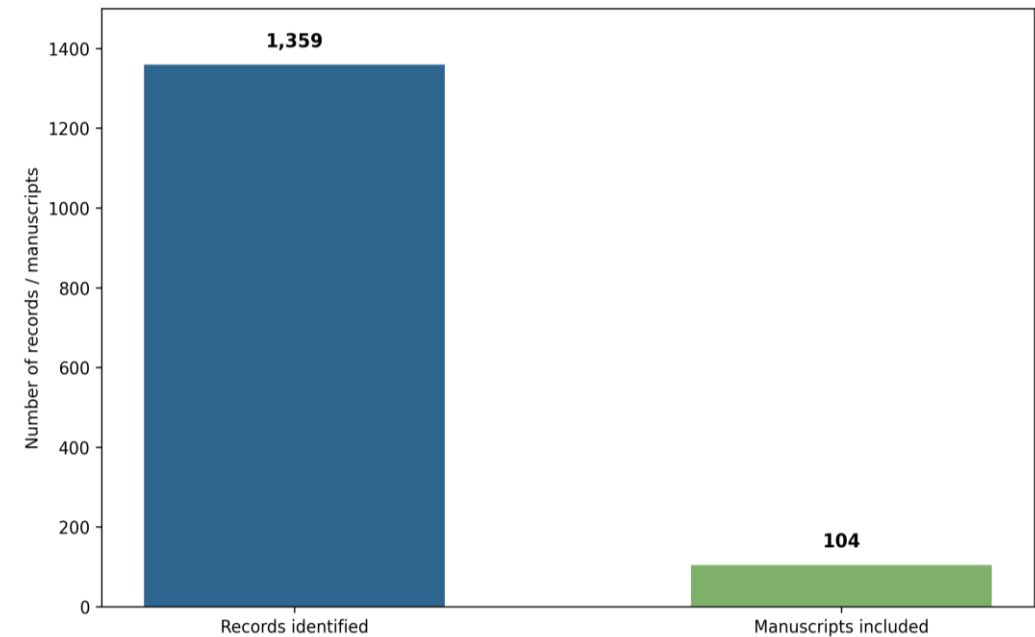
6. Results

The evidence map showed a consistent pattern of rapid methodological diversification accompanied by slower progress in standardisation, validation, representation, and implementation. The strongest quantitative evidence concerned AI growth, telehealth comparative research, audiology data standardisation, and EBP education.

6.1 AI Evidence in Audiology Is Expanding Rapidly

Frosolini et al. (2024) identified 1,359 records across PubMed, Cochrane, and Google Scholar and included 104 manuscripts after screening. The review reported that 87.5% of the included manuscripts had been published during the four years preceding the review, demonstrating pronounced temporal concentration.

Figure 2
AI evidence identified in audiology. The figure presents the 1,359 records identified and the 104 manuscripts included in the scoping review by Frosolini et al. (2024).

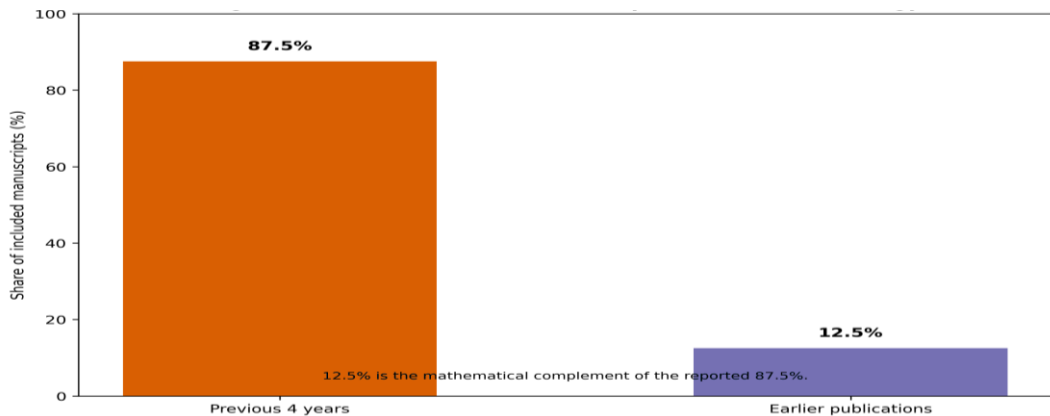


6.2 Recent AI Publications Dominate the Audiology Literature

The reported 87.5% concentration of publications in the preceding four years indicates that AI research in audiology is predominantly contemporary. Figure 3 displays this finding. The 12.5% value is explicitly shown as the mathematical complement of the reported 87.5%; it was not independently reported by Frosolini et al. and should therefore be interpreted only as a derived value.

Figure 3

Concentration of recent AI publications in audiology. The 87.5% value is reported by Frosolini et al. (2024); the 12.5% value is calculated as its mathematical complement.



Koçak (2026) provides independent bibliometric evidence for the same direction of change. The study identified 127 Web of Science-indexed publications from 1995 to 2025, reported marked growth after 2020, and estimated a publication doubling time of approximately 2.1 years. The review further characterised much of the current literature as remaining at proof-of-concept or internally validated stages.

6.3 AI in Speech and Language Research Is Broad but Uneven

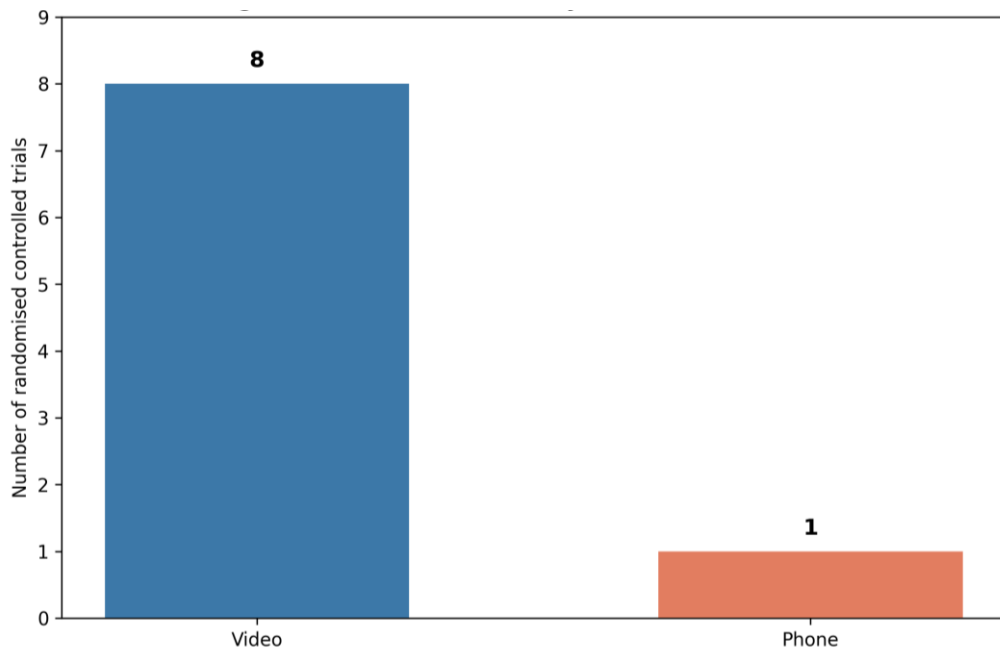
Tbaishat et al. (2025) identified 70 included studies in a systematic mapping study of AI in the diagnosis of speech and language disorders after screening a substantially larger literature. Brahmi et al. (2024) reviewed 65 papers addressing ML-based approaches to speech disorders, with dysarthria representing a major focus and support vector machines and neural-network methods among the frequently used approaches. These findings demonstrate substantial computational activity while also indicating that application areas and methodological maturity are unevenly distributed.

6.4 Telehealth Research Has Progressed Towards Comparative Trials

Scott et al. (2025) identified nine randomised controlled trials, comprising eight video-based trials and one telephone-based trial. Trial sample sizes ranged from 14 to 69 participants, and follow-up ranged from one week to 18 months. For percentage syllables stuttered, the pooled analysis reported a mean difference of 0.1 percentage points (95% CI -0.4 to 0.6; $p = .70$) across relevant follow-up comparisons. For change in monologue sound pressure levels among participants with Parkinson's disease, the reported mean difference was 0.6 (95% CI -1.2 to 2.5; $p = .49$). Four additional trials in speech sound disorder, voice disorder, post-stroke dysphagia, and aphasia reported no differences between telehealth and face-to-face delivery.

Figure 4

Telehealth modality in included speech-language pathology randomised controlled trials. Eight of nine trials evaluated video delivery and one evaluated telephone delivery (Scott et al., 2025).

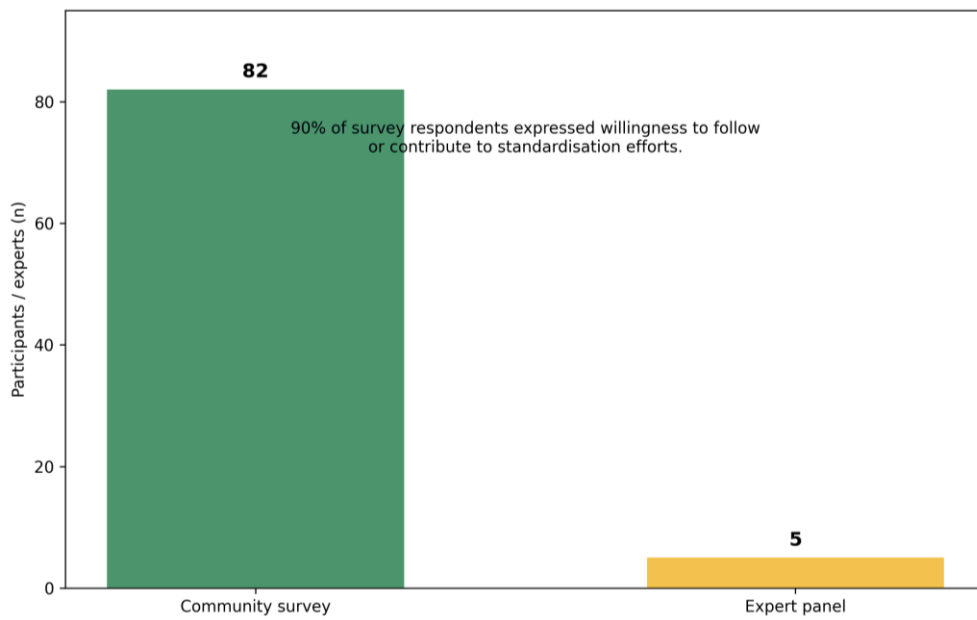


6.5 Audiology Data Standardisation Has Strong Community Support

Vercammen et al. (2026) conducted a mixed-methods investigation incorporating a review of existing standardisation efforts, a global survey, and an expert panel. The survey included 82 members of the computational audiology community and the panel included five experts. Ninety percent of respondents expressed willingness to follow or contribute to standardisation efforts.

Figure 5

Community and expert evidence informing audiology data standardisation.



The figure shows the 82 survey participants and five expert panellists; the reported 90% willingness is presented as an annotation.

The study identified harmonisation as a key challenge while highlighting opportunities to align audiology standards with established health-data approaches, including OMOP, openEHR, and Noah.

6.6 EBP Education Evidence Remains Methodologically Limited

Brock (2026) identified 25 papers describing the teaching of EBP in speech-language pathology programmes and reported 11 different instructional approaches. Common approaches included case-based learning, integration within clinical practicum and coursework, and seminars or modules. However, many programmes used several methods simultaneously, limiting the ability to determine which individual strategies were most effective. The review also highlighted heavy reliance on student self-report and limited objective measurement of learning outcomes.

6.7 Outcome Heterogeneity Remains a Cross-Cutting Constraint

Across measurement research, heterogeneity remains a major limitation. Denman et al. (2017) identified variation in psychometric evidence supporting language assessments. Stark et al. (2021a) demonstrated methodological heterogeneity in aphasia discourse research, while Stark et al. (2021b) documented substantial variation in international practice. These findings indicate that methodological innovation is occurring within an evidence environment in which comparability remains imperfect.

6.8 Overall Evidence Pattern

The integrated evidence map identified four overarching patterns. First, technology-enabled research is expanding rapidly. Second, methodological standards are developing more slowly than technological capabilities. Third, external validation, measurement standardisation, representation, interoperability, and implementation remain recurrent weaknesses. Fourth, clinical translation increasingly depends on contextual factors that are not captured by traditional efficacy or predictive-performance measures alone.

Table 1

Evidence-Synthesis Table

Methodological domain	Key evidence	Principal methodological implication
AI in audiology	1,359 records; 104 included; 87.5% from previous four years	Rapid expansion requires stronger validation and governance
AI in speech/language diagnosis	19,774 papers screened; 70 included	Research is expanding but remains uneven across disorders
Telepractice	9 RCTs; 8 video, 1 telephone	Comparative evidence is emerging, but evidence breadth remains limited
Audiology data standards	82 survey participants; 5 experts; 90% willingness	Standardisation has professional support but requires implementation mechanisms
EBP education	25 papers; 11 instructional approaches	Competency measurement needs to move beyond self-report
Measurement	Persistent heterogeneity across outcomes and methods	Standardised, psychometrically defensible outcomes are necessary
Reproducibility	Multiple reporting standards now available	Transparency should be integral to study design
Cultural/linguistic responsiveness	Persistent representation and adaptation challenges	Generalisability must be evaluated explicitly

7. Integrated Conceptual Framework for Methodological Excellence

The evidence supports an integrated model in which emerging technologies are positioned within, rather than above, the research methodology.

The proposed methodological sequence is: Clinical/Research Problem → Research Question → Theoretical Framework and Paradigm → Design, Sampling and Recruitment

→ Measurement Validity and Reliability → Emerging Methodologies → Transparent Data Management and Analysis → External Validation and Replication → Cultural and Linguistic Responsiveness → Implementation and Clinical Translation → Methodological Excellence.

The model is deliberately sequential but iterative. A poorly specified clinical problem can lead to an inappropriate research question; an ill-defined construct can undermine measurement; weak measurement can compromise model development; inadequate validation can restrict generalisability; and poor implementation planning can prevent clinically meaningful translation. Methodological excellence is therefore conceptualised as the coherence of the complete research pathway rather than the sophistication of an individual statistical or technological component.

8. Discussion

The present synthesis demonstrates that ASLP methodology is undergoing rapid technological diversification, particularly through AI and ML, telepractice, multimodal data, longitudinal analysis, and interoperable research infrastructure. This extends the classical EBP model of integrating evidence with professional expertise and individual preferences by showing that the nature of evidence itself is changing (Sackett et al., 1996). Frosolini et al. (2024) identified 1,359 records and 104 included manuscripts in AI-related audiology research, with 87.5% of included manuscripts appearing within the previous four years. The new methodological interpretation is that the field is generating evidence at a pace that may exceed the rate at which measurement standards, reporting conventions, and validation practices can stabilise. The implication is that methodological governance needs to evolve concurrently with technological innovation rather than after widespread adoption.

The present finding of rapid AI growth is consistent with Koçak's (2026) bibliometric evidence showing 127 publications from 1995 to 2025 and rapid expansion after 2020. Previous literature established the accelerating trajectory; the present synthesis adds the distinction between publication growth and methodological maturity. Koçak's finding that many studies remain at proof-of-concept or internally validated stages indicates that growth in publication volume cannot substitute for evidence of transportability. For ASLP, a model that performs well on a development dataset may not maintain performance across clinics, devices, linguistic populations, age groups, or disease presentations. External validation should consequently be treated as a methodological stage of development rather than an optional confirmation exercise.

The speech and language literature reveals the same tension in a different form. Tbaishat et al. (2025) identified 70 studies in a broad systematic mapping exercise, while Brahmi et al. (2024) found 65 papers focused on ML and speech disorders. Cordella et al. (2025) further demonstrated that the field encompasses a diverse set of computational methods and terminology. The previous literature establishes substantial technical activity; the present synthesis adds that technical diversity increases the importance of consistent reporting and conceptual precision. Classification accuracy, sensitivity, specificity, F1 score, calibration, reliability, and construct validity represent different forms of evidence

and cannot be treated as interchangeable indicators of clinical quality. The implication is that computational ASLP research should report methodological evidence in a layered manner, explicitly distinguishing measurement validity, algorithmic performance, generalisability, and clinical utility.

The telepractice evidence provides a useful example of methodological maturation. Earlier research frequently focused on feasibility, acceptability, and access, whereas Scott et al. (2025) synthesised nine randomised controlled trials and quantified comparative outcomes. The review found no significant differences for several selected outcomes, but also highlighted the small evidence base and limited information on quality of life, well-being, satisfaction, and economic outcomes. The new methodological interpretation is that telepractice should not be evaluated through a single binary model of equivalence. Previous findings indicate that it can deliver comparable outcomes in particular settings; the present synthesis shows why future research needs stratified questions addressing intervention type, patient characteristics, technology, dosage, clinician training, and environmental context. The implication is that pragmatic and implementation-sensitive trials may be more informative than generic comparisons of telehealth versus face-to-face care.

The data-standardisation findings provide a parallel example of methodological infrastructure becoming part of scientific methodology. Vercammen et al. (2026) found 82 survey participants and five expert panellists, with 90% of respondents willing to follow or contribute to standardisation efforts. Earlier FAIR principles emphasised the need for data to be findable, accessible, interoperable, and reusable (Wilkinson et al., 2016), while datasheets and model cards have extended transparency to dataset and model documentation (Geburu et al., 2021; Mitchell et al., 2019). The new contribution of the present synthesis is to connect these infrastructure principles directly with ASLP research scalability. Community willingness provides a necessary social foundation, but interoperability requires sustained governance, versioning, controlled vocabularies, common metadata, and mechanisms for resolving disagreements among standards. The implication is that data standards should be treated as living research infrastructure with explicit stewardship.

Measurement remains the methodological bottleneck across conventional and emerging approaches. The present synthesis is consistent with Denman et al. (2017) and Stark et al. (2021a, 2021b), which demonstrated heterogeneity in language and discourse measurement. Previous psychometric scholarship established the importance of construct validity, reliability, and agreement (Messick, 1995; Cook & Beckman, 2006; Bland & Altman, 1986; Mokkink et al., 2010; Koo & Li, 2016). The new insight is that computational research does not eliminate these requirements; it creates another layer of evidence that must sit on top of them. A highly discriminative model may still be predicting an inadequately defined construct, while a reliable instrument may not be a useful predictor. The implication is that ASLP AI studies should report both psychometric and computational evidence when their systems produce or substitute for clinical measures.

The role of mixed methods also becomes more important as methodological complexity increases. Hryciw et al. (2026) explicitly positioned mixed-methods research as relevant to person-centred and socioculturally sensitive evidence-based practice. Creswell and Plano Clark (2018) previously established that the defining feature of mixed methods is integration, while Yardley (2000) and Braun and Clarke (2006) provided complementary foundations for qualitative rigour and thematic interpretation. The new interpretation is that mixed methods may be particularly appropriate for technology-enabled ASLP research because performance metrics cannot fully explain adoption, trust, acceptability, or contextual fit. The implication is that mixed methods should be considered prospectively when clinical translation depends on both numerical outcomes and stakeholder experience.

The education literature shows that methodological transformation cannot occur sustainably without workforce transformation. Brock (2026) identified 25 papers and 11 instructional approaches for teaching EBP to speech-language pathology students, but found substantial reliance on self-report and limited objective outcomes. Greenwell and Walsh (2021) similarly identified practical barriers to EBP use. The present synthesis therefore extends the problem from EBP education to methodological readiness for AI-era research. Future ASLP professionals need not become specialist programmers, but they require sufficient knowledge to interrogate sampling, validity, statistical assumptions, model claims, data provenance, bias, external validation, and clinical utility. The implication is that methodological literacy should encompass AI and data literacy in addition to conventional EBP skills.

Cultural and linguistic responsiveness is likewise not a peripheral concern. Sinclair et al. (2025) and Medina et al. (2022) demonstrate continuing challenges in culturally and linguistically diverse ASLP contexts, while Bampoe et al. (2025) illustrate how locally grounded assessment development can address these limitations. Previous research establishes the need for context-sensitive assessment; the present synthesis adds that AI can amplify the consequences of underrepresentation because a dataset can encode systematic differences at scale. The implication is that representativeness must be assessed at the dataset, algorithmic, measurement, and implementation levels. Reporting only aggregate accuracy can obscure meaningful subgroup disparities.

Reproducibility represents a common thread across the methodological transition. Reporting frameworks such as CONSORT 2010, STROBE, COREQ, SRQR, PRISMA-ScR, SPIRIT-AI, CONSORT-AI, and TRIPOD+AI provide increasingly specific expectations for transparent reporting (Schulz et al., 2010; von Elm et al., 2007; Tong et al., 2007; O'Brien et al., 2014; Tricco et al., 2018; Rivera et al., 2020; Liu et al., 2020; Collins et al., 2024). Earlier work on reproducibility in hearing research and responsible ML reinforces the need for transparent methods and reproducible pipelines (Heinrich & Knight, 2020; Wiens et al., 2019). The new interpretation is that reproducibility should be treated as an architectural property of research rather than a reporting task added at manuscript preparation. The implication is that study protocols, code, metadata, model documentation, and analytical decisions should be planned with future verification in mind.

Implementation is the final link between methodological validity and real-world impact. Proctor et al. (2011) distinguished implementation outcomes from clinical outcomes, while Greenhalgh et al. (2017) showed that technology adoption is influenced by interacting individual, organisational, and system-level factors. Damschroder et al. (2022) further updated the CFIR to reflect stakeholder feedback and equity-related determinants. The present synthesis brings these approaches into ASLP methodology by arguing that implementation should be considered during study design, not after efficacy evidence has been generated. A method that is accurate but unacceptable, inaccessible, costly, difficult to maintain, or poorly aligned with workflow may have limited practical effect. The implication is that implementation outcomes should increasingly be incorporated into ASLP technology research alongside clinical outcomes.

The cumulative evidence therefore supports a redefinition of methodological excellence. Historically, methodological quality was often centred on study design, statistical validity, and reporting completeness. Contemporary ASLP research additionally requires interoperability, computational transparency, external validation, subgroup assessment, implementation readiness, and cultural and linguistic responsiveness. The proposed framework synthesises these requirements into an end-to-end model in which technology is one component of a larger evidence-generating system. The implication is that the quality of a study should ultimately be determined by the coherence of its full methodological pathway—from the clinical problem through measurement and analysis to reproducible, interpretable, and implementable evidence.

9. Recommendations

The evidence supports coordinated methodological development across research design, measurement, technology, data governance, education, and implementation. The following recommendations translate the synthesis into actions that can be applied by ASLP researchers, academic programmes, clinicians, research institutions, professional organisations, and journals.

- Align methodological choice with the research question. Study design, measurement, analysis, and technology should be selected because they appropriately answer the research question rather than because a method is novel or technically sophisticated.
- Require independent or external validation for clinically oriented AI models. Computational systems intended for clinical use should be evaluated on independent populations, sites, devices, or linguistic contexts whenever feasible.
- Strengthen psychometric evaluation of technology-enabled measures. AI-derived, digital, and automated outcomes should be examined for validity, reliability, responsiveness, and interpretability before they are used as substitutes for established clinical measures.
- Develop interoperable ASLP data infrastructures. Common data dictionaries, metadata structures, ontologies, coding schemes, provenance documentation, and

quality-control procedures should be incorporated into collaborative research.

- Embed cultural and linguistic responsiveness throughout the research process. Representation should be addressed during research question formulation, sampling, instrument selection, annotation, model development, validation, and implementation.
- Use mixed methods when clinical meaning depends on context. Quantitative outcomes should be integrated with patient, caregiver, clinician, and implementation perspectives when those dimensions influence interpretation.
- Improve transparency in computational research. Publications should provide sufficient information on datasets, preprocessing, model development, training and testing procedures, validation, missing data, performance metrics, and intended use.
- Evaluate clinical utility in addition to statistical performance. AI and digital-health studies should consider acceptability, safety, workflow integration, equity, cost, sustainability, and patient-centred outcomes.
- Modernise methodological education in ASLP. Curricula should include evidence synthesis, psychometrics, statistics, reproducibility, data governance, AI literacy, critical appraisal, and implementation science.
- Establish collaborative methodological standards. Standardisation initiatives should involve researchers, clinicians, statisticians, data scientists, service users, and relevant professional organisations and should include mechanisms for maintenance and revision.

10. Future Directions

The next stage of ASLP research is likely to involve interconnected systems rather than isolated technologies. AI, telepractice, multimodal assessment, longitudinal monitoring, digital biomarkers, and interoperable datasets are increasingly converging. Methodological development should therefore focus on infrastructures and standards that allow these components to interact without sacrificing validity, equity, or interpretability.

- Develop federated and privacy-preserving research networks that enable multi-site computational research while limiting unnecessary centralisation of sensitive clinical data.
- Create benchmark datasets and common evaluation protocols for major ASLP computational tasks to improve comparability between studies.
- Prioritise prospective external-validation studies before computational systems are positioned as clinically ready.
- Expand longitudinal and real-world outcome research so that treatment response, participation, adherence, and communication behaviour can be evaluated beyond controlled research settings.

- Evaluate digital biomarkers through measurement science rather than assuming that continuously collected or automatically generated variables are clinically valid.
- Build equity-aware AI pipelines in which subgroup representation and subgroup performance are explicitly reported.
- Integrate implementation science earlier in technology development so that workflow, workforce, sustainability, and organisational determinants are considered before large-scale deployment.
- Strengthen reproducible research infrastructures through documented code, version control, transparent preprocessing, model cards, dataset documentation, and appropriate data-sharing mechanisms.
- Develop global methodological competencies for ASLP professionals so that clinicians and researchers can critically interpret AI, digital health, statistical, and evidence-synthesis claims.
- Establish an international consensus framework for ASLP methodological excellence covering research design, measurement, AI reporting, data standardisation, cultural and linguistic responsiveness, reproducibility, and implementation.

11. Conclusion

Research methodology in Audiology and Speech-Language Pathology is undergoing a substantial transformation. AI and ML are expanding rapidly; telepractice is moving towards comparative effectiveness research; mixed methods are increasingly relevant to person-centred and context-sensitive evidence; multimodal and longitudinal approaches are broadening the range of measurable outcomes; and data standardisation is emerging as an essential component of computational research infrastructure.

At the same time, methodological weaknesses remain evident. Outcome heterogeneity continues to restrict evidence synthesis. Computational studies frequently require stronger external validation and clearer reporting. Data interoperability remains incomplete. Cultural and linguistic representation requires greater methodological attention. EBP education often lacks objective measures of learning. Most importantly, technological performance does not guarantee clinical value.

The central conclusion is therefore that technological innovation and methodological excellence are not synonymous. Methodological excellence is achieved when the research question, theoretical paradigm, design, sampling, measurement, analysis, data governance, validation, contextual responsiveness, implementation, and clinical interpretation are coherent and transparent. AI, digital health, telepractice, and multimodal research should consequently be understood as methodological tools embedded within a broader evidence-generating system.

The integrated framework proposed in this paper provides a practical basis for that

system. It moves ASLP research from technology-centred innovation towards methodology-centred innovation: innovation that is rigorous, reproducible, interoperable, culturally responsive, implementation-aware, and clinically meaningful. This orientation can help ensure that future technological advances strengthen rather than weaken the evidential foundations of Audiology and Speech-Language Pathology.

References

- Bampoe, J. O., Verdon, S. E., Hoffman, L., & Wylie, K. (2025). Speech-language pathologists' perspectives on a prototype of the first Ghanaian-English speech and language assessment tool. *International Journal of Speech-Language Pathology*. <https://doi.org/10.1080/17549507.2025.2542459>
- Bland, J. M., & Altman, D. G. (1986). Statistical methods for assessing agreement between two methods of clinical measurement. *The Lancet*, 1(8476), 307-310. [https://doi.org/10.1016/S0140-6736\(86\)90837-8](https://doi.org/10.1016/S0140-6736(86)90837-8)
- Brahmi, Z., Mahyoob, M., Al-Sarem, M., Algaraady, J., Bousselmi, K., & Alblwi, A. (2024). Exploring the role of machine learning in diagnosing and treating speech disorders: A systematic literature review. *Psychology Research and Behavior Management*, 17, 2205-2232. <https://doi.org/10.2147/PRBM.S460283>
- Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77-101. <https://doi.org/10.1191/1478088706qp063oa>
- Brock, A. S. (2026). Exploring the state of the literature on teaching evidence-based practice to speech-language pathology students: A scoping review. *American Journal of Speech-Language Pathology*, 35(5), 2417-2433. https://doi.org/10.1044/2026_AJSLP-25-00227
- Collins, G. S., Moons, K. G. M., Dhiman, P., Riley, R. D., Beam, A. L., Van Calster, B., Ghassemi, M., Liu, X., Reitsma, J. B., van Smeden, M., Boulesteix, A.-L., Camaradou, J.-C., Celi, L. A., Denaxas, S., Denniston, A. K., Glocker, B., Golub, R. M., Harvey, H., Heinze, G., ... Logullo, P. (2024). TRIPOD+AI statement: Updated guidance for reporting clinical prediction models that use regression or machine learning methods. *BMJ*, 385, e078378. <https://doi.org/10.1136/bmj-2023-078378>
- Cook, D. A., & Beckman, T. J. (2006). Current concepts in validity and reliability for psychometric instruments: Theory and application. *The American Journal of Medicine*, 119(2), 166.e7-166.e16. <https://doi.org/10.1016/j.amjmed.2005.10.036>
- Cordella, C., Marte, M. J., Liu, H., & Kiran, S. (2025). An introduction to machine learning for speech-language pathologists: Concepts, terminology, and emerging applications. *Perspectives of the ASHA Special Interest Groups*, 10(2), 432-450. https://doi.org/10.1044/2024_PERSP-24-00037
- Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research* (3rd ed.). SAGE Publications.
- Damschroder, L. J., Aron, D. C., Keith, R. E., Kirsh, S. R., Alexander, J. A., & Lowery, J. C. (2009). Fostering implementation of health services research findings into practice: A consolidated framework for advancing implementation science. *Implementation Science*, 4, Article 50. <https://doi.org/10.1186/1748-5908-4-50>
- Damschroder, L. J., Reardon, C. M., Widerquist, M. A. O., & Lowery, J. (2022). The updated Consolidated Framework for Implementation Research based on user feedback. *Implementation Science*, 17, Article 75. <https://doi.org/10.1186/s13012-022-01245-0>
- Denman, D., Speyer, R., Munro, N., Pearce, W. M., Chen, Y.-W., & Cordier, R. (2017). Psychometric properties of language assessments for children aged 4-12 years: A systematic review. *Frontiers in Psychology*, 8, Article 1515. <https://doi.org/10.3389/fpsyg.2017.01515>
- Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., Cui, C., Corrado, G., Thrun, S., & Dean, J. (2019). A guide to deep learning in healthcare. *Nature Medicine*, 25, 24-29. <https://doi.org/10.1038/s41591-018-0316-z>

- Frosolini, A., Franz, L., Caragli, V., Genovese, E., de Filippis, C., & Marioni, G. (2024). Artificial intelligence in audiology: A scoping review of current applications and future directions. *Sensors*, 24(22), Article 7126. <https://doi.org/10.3390/s24227126>
- Gebru, T., Morgenstern, J., Vecchione, B., Vaughan, J. W., Wallach, H., Daumé, H., III, & Crawford, K. (2021). Datasheets for datasets. *Communications of the ACM*, 64(12), 86-92. <https://doi.org/10.1145/3458723>
- Glasgow, R. E., Harden, S. M., Gaglio, B., Rabin, B., Smith, M. L., Porter, G. C., Ory, M. G., & Estabrooks, P. A. (2019). RE-AIM planning and evaluation framework: Adapting to new science and practice with a 20-year review. *Frontiers in Public Health*, 7, Article 64. <https://doi.org/10.3389/fpubh.2019.00064>
- Greenhalgh, T., Wherton, J., Papoutsis, C., Lynch, J., Hughes, G., A'Court, C., Hinder, S., Fahy, N., Procter, R., & Shaw, S. (2017). Beyond adoption: A new framework for theorising and evaluating nonadoption, abandonment, and challenges to the scale-up, spread, and sustainability of health and care technologies. *Journal of Medical Internet Research*, 19(11), Article e367. <https://doi.org/10.2196/jmir.8775>
- Greenwell, T., & Walsh, B. (2021). Evidence-based practice in speech-language pathology: Where are we now? *American Journal of Speech-Language Pathology*, 30(1), 186-198. https://doi.org/10.1044/2020_AJSLP-20-00194
- Heinrich, A., & Knight, M. (2020). Reproducibility in cognitive hearing research. *Frontiers in Psychology*, 11, Article 1590. <https://doi.org/10.3389/fpsyg.2020.01590>
- Hryciw, T., Charest, M., & Filiatrault-Veilleux, P. (2026). Using mixed methods research to guide evidence-based practice in speech-language pathology interventions. *International Journal of Speech-Language Pathology*, 1-14. <https://doi.org/10.1080/17549507.2026.2667826>
- Koçak, C. A. (2026). Artificial intelligence and machine learning in audiology and hearing disorders: A scoping review with bibliometric and thematic mapping (1995-2025). *Audiology Research*, 16(2), Article 29. <https://doi.org/10.3390/audiolres16020029>
- Koo, T. K., & Li, M. Y. (2016). A guideline of selecting and reporting intraclass correlation coefficients for reliability research. *Journal of Chiropractic Medicine*, 15(2), 155-163. <https://doi.org/10.1016/j.jcm.2016.02.012>
- Liu, X., Cruz Rivera, S., Moher, D., Calvert, M. J., Denniston, A. K., & the SPIRIT-AI and CONSORT-AI Working Group. (2020). Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: The CONSORT-AI extension. *Nature Medicine*, 26, 1364-1374. <https://doi.org/10.1038/s41591-020-1034-x>
- Medina, A. M., Alfano, A. R., & Moore, S. (2022). Considerations for addressing the needs of culturally and linguistically diverse speech-language pathology Praxis test takers. *American Journal of Speech-Language Pathology*, 31(2), 601-612. https://doi.org/10.1044/2021_AJSLP-20-00358
- Messick, S. (1995). Validity of psychological assessment: Validation of inferences from persons' responses and performances as scientific inquiry into score meaning. *American Psychologist*, 50(9), 741-749. <https://doi.org/10.1037/0003-066X.50.9.741>
- Michie, S., van Stralen, M. M., & West, R. (2011). The behaviour change wheel: A new method for characterising and designing behaviour change interventions. *Implementation Science*, 6, Article 42. <https://doi.org/10.1186/1748-5908-6-42>
- Mitchell, M., Wu, S., Zaldivar, A., Barnes, P., Vasserman, L., Hutchinson, B., Spitzer, E., Raji, I. D., & Gebu, T. (2019). Model cards for model reporting. In *Proceedings of the Conference on Fairness, Accountability, and Transparency* (pp. 220-229). Association for Computing Machinery. <https://doi.org/10.1145/3287560.3287596>
- Mokkink, L. B., Terwee, C. B., Patrick, D. L., Alonso, J., Stratford, P. W., Knol, D. L., Bouter, L. M., & de Vet, H. C. W. (2010). The COSMIN checklist for evaluating the methodological quality of studies on measurement properties of health status measurement instruments: An international Delphi study. *Quality of Life Research*, 19, 539-549. <https://doi.org/10.1007/s11136-010-9606-8>

- Nudelman, C. J., Tardini, V., & Bottalico, P. (2025). Artificial intelligence to detect voice disorders. *Journal of Voice*. Advance online publication. <https://doi.org/10.1016/j.jvoice.2025.09.021>
- O'Brien, B. C., Harris, I. B., Beckman, T. J., Reed, D. A., & Cook, D. A. (2014). Standards for reporting qualitative research: A synthesis of recommendations. *Academic Medicine*, 89(9), 1245-1251. <https://doi.org/10.1097/ACM.0000000000000388>
- Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, 366(6464), 447-453. <https://doi.org/10.1126/science.aax2342>
- Palomares-Aguilera, M., Inostroza-Allende, F., & Riquelme Solar, L. (2021). Speech pathology telepractice intervention during the COVID-19 pandemic for Spanish-speaking children with cleft palate: A systematic review. *International Journal of Pediatric Otorhinolaryngology*, 144, Article 110700. <https://doi.org/10.1016/j.ijporl.2021.110700>
- Peters, M. D. J., Marnie, C., Tricco, A. C., Pollock, D., Munn, Z., Alexander, L., McInerney, P., Godfrey, C. M., & Khalil, H. (2020). Updated methodological guidance for the conduct of scoping reviews. *JBIM Evidence Synthesis*, 18(10), 2119-2126. <https://doi.org/10.11124/JBIES-20-00167>
- Prinsen, C. A. C., Mokkink, L. B., Bouter, L. M., Alonso, J., Patrick, D. L., de Vet, H. C. W., & Terwee, C. B. (2018). COSMIN guideline for systematic reviews of patient-reported outcome measures. *Quality of Life Research*, 27, 1147-1157. <https://doi.org/10.1007/s11136-018-1798-3>
- Proctor, E., Silmere, H., Raghavan, R., Hovmand, P., Aarons, G., Bunger, A., Griffey, R., & Hensley, M. (2011). Outcomes for implementation research: Conceptual distinctions, measurement challenges, and research agenda. *Administration and Policy in Mental Health and Mental Health Services Research*, 38(2), 65-76. <https://doi.org/10.1007/s10488-010-0319-7>
- Rivera, S. C., Liu, X., Chan, A.-W., Denniston, A. K., & Calvert, M. J. (2020). Guidelines for clinical trial protocols for interventions involving artificial intelligence: The SPIRIT-AI extension. *Nature Medicine*, 26, 1351-1363. <https://doi.org/10.1038/s41591-020-1037-7>
- Sackett, D. L., Rosenberg, W. M. C., Gray, J. A. M., Haynes, R. B., & Richardson, W. S. (1996). Evidence based medicine: What it is and what it isn't. *BMJ*, 312(7023), 71-72. <https://doi.org/10.1136/bmj.312.7023.71>
- Schulz, K. F., Altman, D. G., & Moher, D. (2010). CONSORT 2010 statement: Updated guidelines for reporting parallel group randomised trials. *BMJ*, 340, Article c332. <https://doi.org/10.1136/bmj.c332>
- Scott, A. M., Clark, J., Cardona, M., Atkins, T., Peiris, R., Greenwood, H., Wenke, R., Cardell, E., & Glasziou, P. (2025). Telehealth versus face-to-face delivery of speech language pathology services: A systematic review and meta-analysis. *Journal of Telemedicine and Telecare*, 31(9), 1203-1215. <https://doi.org/10.1177/1357633X241272976>
- Sinclair, R. L., Finke, E. H., & Wu, L. (2025). Speech-language pathologists' experiences working with culturally and linguistically diverse families. *American Journal of Speech-Language Pathology*, 34(2), 908-930. https://doi.org/10.1044/2024_AJSLP-24-00185
- Stark, B. C., Dutta, M., Murray, L. L., Bryant, L., Fromm, D., MacWhinney, B., Ramage, A. E., Roberts, A. C., den Ouden, D. B., Brock, K., McKinney-Bock, K., Paek, E. J., Harmon, T. G., Yoon, S. I., Themistocleous, C., Yoo, H., Aveni, K., Gutierrez, S., & Sharma, S. (2021a). Standardizing assessment of spoken discourse in aphasia: A working group with deliverables. *American Journal of Speech-Language Pathology*, 30(1S), 491-502. https://doi.org/10.1044/2020_AJSLP-19-00093
- Stark, B. C., Dutta, M., Murray, L. L., Fromm, D., Bryant, L., Harmon, T. G., Ramage, A. E., & Roberts, A. C. (2021b). Spoken discourse assessment and analysis in aphasia: An international survey of current practices. *Journal of Speech, Language, and Hearing Research*, 64(11), 4366-4389. https://doi.org/10.1044/2021_JSLHR-20-00708
- Tbaishat, D., Al-Shafei, R., & Odeh, M. (2025). The role of AI in the diagnosis of speech and language disorders: A systematic mapping study. *Digital Health*, 11, Article 20552076251379769. <https://doi.org/10.1177/20552076251379769>

- Terwee, C. B., Bot, S. D. M., de Boer, M. R., van der Windt, D. A. W. M., Knol, D. L., Dekker, J., Bouter, L. M., & de Vet, H. C. W. (2007). Quality criteria were proposed for measurement properties of health status questionnaires. *Journal of Clinical Epidemiology*, 60(1), 34-42. <https://doi.org/10.1016/j.jclinepi.2006.03.012>
- Tong, A., Sainsbury, P., & Craig, J. (2007). Consolidated criteria for reporting qualitative research (COREQ): A 32-item checklist for interviews and focus groups. *International Journal for Quality in Health Care*, 19(6), 349-357. <https://doi.org/10.1093/intqhc/mzm042>
- Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine*, 25, 44-56. <https://doi.org/10.1038/s41591-018-0300-7>
- Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., Moher, D., Peters, M. D. J., Horsley, T., Weeks, L., Hempel, S., Akl, E. A., Chang, C., McGowan, J., Stewart, L., Hartling, L., Aldcroft, A., Wilson, M. G., Garritty, C., ... Straus, S. E. (2018). PRISMA extension for scoping reviews (PRISMA-ScR): Checklist and explanation. *Annals of Internal Medicine*, 169(7), 467-473. <https://doi.org/10.7326/M18-0850>
- Varma, M., Nayak, S., Rao, R. R., & Devadas, U. (2025). Effectiveness of teletherapy in managing voice disorders: A systematic review. *Indian Journal of Otolaryngology and Head & Neck Surgery*, 77(8), 3320-3336. <https://doi.org/10.1007/s12070-025-05775-z>
- Vercammen, C., Heinrich, A., Lesimple, C., Paglialonga, A., Wasmann, J.-W. A., & Buhl, M. (2026). Data standards in audiology: A mixed-methods exploration of community perspectives and implementation considerations. *International Journal of Audiology*, 1-17. <https://doi.org/10.1080/14992027.2026.2619921>
- Walters, J., Bryant, L., & Hemsley, B. (2025). A systematic review of evidence relating to the use of telesupervision for speech-language pathology students on clinical placements. *International Journal of Language & Communication Disorders*, 60(1), Article e13133. <https://doi.org/10.1111/1460-6984.13133>
- Whitehorn, A., Porritt, K., Lockwood, C., Xing, W., Zhu, Z., & Hu, Y. (2020). Methodological components and quality of evidence summaries: A scoping review protocol. *JBISIRIR-D-19-00258*. <https://doi.org/10.11124/JBISIRIR-D-19-00258>
- Wiens, J., Saria, S., Sendak, M., Ghassemi, M., Liu, V. X., Doshi-Velez, F., Jung, K., Heller, K., Kale, D., Saeed, M., Ossorio, P. N., Thadaney-Israni, S., & Goldenberg, A. (2019). Do no harm: A roadmap for responsible machine learning for health care. *Nature Medicine*, 25, 1337-1340. <https://doi.org/10.1038/s41591-019-0548-6>
- Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J. J., Appleton, G., Axton, M., Baak, A., Blomberg, N., Boiten, J.-W., Bonino da Silva Santos, L., Bourne, P. E., Bouwman, J., Brookes, A. J., Clark, T., Crosas, M., Dillo, I., Dumon, O., Edmunds, S., Evelo, C. T., Finkers, R., & Mons, B. (2016). The FAIR guiding principles for scientific data management and stewardship. *Scientific Data*, 3, Article 160018. <https://doi.org/10.1038/sdata.2016.18>
- World Health Organization. (2021). *Ethics and governance of artificial intelligence for health: WHO guidance*.
- Yardley, L. (2000). Dilemmas in qualitative health research. *Psychology & Health*, 15(2), 215-228. <https://doi.org/10.1080/08870440008400302>