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Artificial Intelligence-Based Assessment and Intervention for Specific Learning Disabilities: A Systematic Review

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A B S T R A C T

Objective: This study aimed to systematically review the existing evidence on the application of artificial intelligence-based methods in the assessment, screening, prediction, diagnosis, intervention, and progress monitoring of specific learning disabilities.

Methods and Materials: This systematic review was conducted according to PRISMA-based principles. Scientific databases including Scopus, Web of Science, PubMed/MEDLINE, ERIC, PsycINFO, IEEE Xplore, and ScienceDirect were searched for studies published between January 2014 and May 2026. The search combined terms related to artificial intelligence, machine learning, deep learning, expert systems, adaptive learning, intelligent tutoring, dyslexia, dyscalculia, dysgraphia, and specific learning disabilities. From 1,286 initially identified records, 362 duplicates were removed, 924 titles and abstracts were screened, and 153 full-text articles were assessed for eligibility. Finally, 42 studies met the inclusion criteria and were analyzed through descriptive and narrative synthesis.

Findings: Inferential synthesis of the included studies indicated that artificial intelligence-based models showed the strongest evidence in assessment-related functions, particularly early screening, diagnostic classification, and academic-risk prediction. Classification and prediction models generally demonstrated acceptable to high performance, especially when multidimensional cognitive, linguistic, academic, behavioral, handwriting, or digital-learning data were used. Evidence was strongest for dyslexia and reading disorder, while dyscalculia and dysgraphia were less frequently investigated but showed promising results, particularly in handwriting analysis and mathematics-risk detection. Intervention-related findings indicated that AI-based adaptive learning systems, intelligent tutoring platforms, mobile applications, serious games, and personalized feedback tools were associated with improvement in short-term academic outcomes, especially reading accuracy, decoding, mathematical performance, writing accuracy, engagement, and progress monitoring. However, evidence for long-term intervention effectiveness, transfer, and sustained educational outcomes remained limited.

Conclusion: Artificial intelligence has considerable potential to support the early identification, individualized assessment, adaptive intervention, and continuous monitoring of learners with specific learning disabilities. Nevertheless, current evidence is stronger for screening and classification than for intervention effectiveness. Future studies should prioritize external validation, longitudinal designs, explainability, ethical implementation, cultural adaptation, and integration with professional educational and clinical judgment.

Keywords: *Artificial intelligence; specific learning disabilities; dyslexia; dyscalculia; dysgraphia; machine learning; adaptive intervention; systematic review.*

1. Introduction

Specific learning disabilities constitute a major area of concern in educational psychology, neurodevelopmental research, child mental health, and inclusive education because they affect the acquisition and use of foundational academic skills despite the presence of adequate learning opportunities, conventional instruction, and generally preserved intellectual potential. These conditions are most commonly expressed through persistent impairments in reading, written expression, spelling, handwriting, mathematical reasoning, numerical processing, or broader academic performance, and they frequently emerge during the early years of schooling when formal literacy and numeracy demands increase. Specific learning disabilities are not merely academic difficulties; rather, they are complex developmental conditions that may interact with cognitive processing, executive functioning, memory, language, attention, emotional adjustment, classroom participation, and long-term educational trajectories. Contemporary scholarship increasingly emphasizes that these disabilities should be understood through an integrated framework that connects neuroscience, educational practice, psychosocial support, and technology-based innovation, because conventional assessment and intervention systems often fail to provide timely, individualized, and scalable responses to learners' needs (Asdaq et al., 2025; Mohamed et al., 2026). The importance of this issue becomes even more evident in low-resource or crisis-affected contexts, where children with learning disabilities may experience psychosocial vulnerability, educational exclusion, stigmatization, and reduced access to specialized services, as demonstrated in research on children in South Sudanese refugee-camp settings (Achiek & Selugo, 2024). Therefore, the assessment and intervention of specific learning disabilities represent not only a clinical or educational challenge but also a broader matter of equity, participation, and child development.

The conceptualization of specific learning disabilities has expanded considerably in recent years. Earlier approaches often focused primarily on observable academic underachievement, whereas contemporary models emphasize multiple interacting mechanisms, including phonological processing, working memory, attentional control, language development, visuospatial processing, rhythm perception, motor coordination, and neural organization. For example, dyscalculia has been associated with working-memory limitations and atypical numerical or spatial processing, indicating that mathematics-related learning difficulties cannot be understood only as poor arithmetic performance (Galitskaya & Drigas, 2021). Similarly, evidence regarding rhythm perception deficits in children with specific learning disabilities suggests that temporal processing and auditory-motor integration may contribute to learning profiles, particularly in relation to reading, language, and academic performance (Hande & Hegde, 2021). Research on common neural substrates across diverse neurodevelopmental disorders further supports the view that learning disabilities overlap with broader neurodevelopmental systems, rather than existing as isolated academic problems (Sokolowski & Levine, 2022). At the same time, genetic and biological investigations, including studies of candidate-gene variation in families affected by specific learning disorders, show that the etiology of these conditions is multifactorial and may include inherited, neurobiological, cognitive, and environmental influences (Calì et al., 2023). These findings collectively indicate that valid assessment requires multidimensional data and that effective intervention must be responsive to the heterogeneity of learners' cognitive and academic profiles.

Among specific learning disabilities, dyslexia has received the greatest research attention, particularly because reading is central to academic success across school subjects and because reading difficulties are often detectable through measurable patterns in phonological awareness, decoding, fluency, spelling, eye movement, response time, and written language. Bibliometric evidence on early predictors of language-based learning disabilities indicates the increasing research interest in identifying reliable markers before difficulties become entrenched and lead to cumulative educational failure (Alabbad et al., 2023). Machine learning research on dyslexia detection has further emphasized the importance of feature selection, algorithm selection, and evaluation metrics in developing accurate prediction systems (Parvathy, 2023). Studies using checklist, questionnaire, and online game-based datasets have shown that dyslexia-related risk can be explored through different forms of learner data, including self-report, teacher observation, and performance within digital environments (Santhiya & Kanimozhiselvi, 2023). Expert-system approaches have also been applied to the early diagnosis of dyslexia, including certainty-factor models designed to translate symptom profiles into probabilistic diagnostic support (Ashidiqi et al., 2023). These developments illustrate a significant shift from static paper-based assessment toward computationally supported systems that can process multiple indicators, support early screening, and provide more systematic decision-making support for educators and clinicians.

Although dyslexia remains the most extensively studied learning disability in artificial intelligence research, increasing attention has also been directed toward dyscalculia and dysgraphia. Dyscalculia is particularly important because difficulties in number sense, calculation, arithmetic fluency, and mathematical reasoning can interfere with academic progress, daily functioning, and later vocational opportunities. Recent surveys of AI-enhanced dyscalculia screening highlight the growing use of computational methods for identifying mathematical learning problems in children and for distinguishing dyscalculia-related patterns from general low achievement (Bhushan et al., 2024). Dysgraphia has likewise become an important domain for AI-supported assessment because handwriting, spelling, written expression, motor control, and written-production fluency can generate rich behavioral and digital traces. Automated systems for diagnosing dysgraphia increasingly use handwriting features, document analysis, online writing data, image-based processing, and machine learning frameworks (Kunhoth et al., 2024). Convolutional neural network methods have been proposed for dysgraphia detection, demonstrating the potential of deep learning to classify handwriting-related abnormalities from visual or graphical data (Škunda et al., 2022). More recent multimodal approaches for dysgraphia risk assessment, including work with Sinhala-speaking children, show that language-specific, script-specific, and culturally contextualized AI models may be necessary because written expression and handwriting are shaped by orthography, educational practice, and linguistic structure (Weraduwa et al., 2025). In addition, comprehensive scoping work on AI-driven dysgraphia diagnosis using online and offline handwriting data confirms that the field is moving toward integrated systems capable of combining dynamic writing behavior with static written outputs (Fallah, 2025).

Artificial intelligence has become increasingly relevant to specific learning disabilities because it offers methodological capacities that are difficult to achieve through conventional assessment alone. AI-based systems can process large datasets, identify complex nonlinear patterns, classify learners according to risk or diagnostic profiles, integrate heterogeneous sources of data, and provide automated or semi-automated feedback. Weighted ensemble learning models, for example, have been proposed for the identification of specific learning disability, suggesting that combining multiple classifiers may improve diagnostic robustness and reduce the limitations associated with single-model approaches (Alzahrani & Algahtani, 2024). Expert systems for diagnosing learning disorders in children similarly demonstrate how rule-based and knowledge-based computational approaches can support clinical or educational decision-making when specialist access is limited (Andrade-Arenas & Yactayo-Arias, 2024). Earlier expert-system work on school-age children also indicates that learning-disability classification can be formalized through structured symptom and performance indicators, allowing educational professionals to use technology for preliminary categorization and referral support (Fajariyanti et al., 2022). Such systems are not intended to replace psychoeducational assessment, clinical judgment, or individualized case formulation; however, they may strengthen early identification, reduce delays in referral, and support more consistent screening practices. The promise of AI is particularly significant in settings where specialized assessment is expensive, geographically inaccessible, or dependent on limited professional resources.

In addition to assessment and diagnosis, artificial intelligence and related digital technologies are increasingly being explored as intervention tools for learners with specific learning disabilities. AI-supported intervention systems may include intelligent tutoring systems, adaptive learning platforms, mobile applications, serious games,

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exergames, automated feedback tools, learning analytics dashboards, and digital environments that adjust task difficulty according to learner performance. Mobile applications have been investigated as tools for treating learning difficulties among students, with attention to their accessibility, interactivity, and capacity to provide individualized practice outside conventional classroom settings (Alzubi, 2023). Systematic analysis of AI-empowered educational tools developed in India for disabled people further suggests that digital technologies may support inclusion when they are designed around accessibility, usability, and learner diversity (Gupta & Gupta, 2024). Serious gaming and technology-based approaches have also been examined in relation to neurodevelopmental disorders, including their potential roles in screening, monitoring, diagnosis, and treatment (Shaikh et al., 2024; Shaikh et al., 2025). Exergames, meanwhile, have been considered for their possible influence on executive functions and academic performance in school-age children with specific learning disorder, reflecting a broader understanding of intervention that includes cognition, movement, motivation, and engagement (Coacci et al., 2023). These approaches are important because children with learning disabilities often require repeated practice, immediate feedback, motivational support, and adaptive learning sequences that are difficult to deliver consistently in traditional classrooms.

The intervention literature also includes neurocognitive and neurostimulation-based approaches that intersect with technology-supported learning-disability management. Neurofeedback has been reviewed in the education of children with attention-deficit/hyperactivity disorder and specific learning disorders, showing interest in interventions that target self-regulation, attention, and neurocognitive functioning rather than academic skills alone (Patil et al., 2022). Transcranial electrical stimulation interventions have also been reviewed in children and adolescents with specific learning disabilities, indicating growing interest in technology-assisted cognitive enhancement and the modulation of learning-related neural systems (Azar et al., 2024). Related work on transcranial direct current stimulation in ADHD and co-occurring conditions highlights the broader clinical interest in neuromodulation for neurodevelopmental profiles that often overlap with learning disabilities (Ali et al., 2023). Attention training has also been systematically reviewed in specific learning disorders, with transfer analysis emphasizing whether cognitive training effects extend beyond trained tasks into broader academic or functional outcomes (Nejati et al., 2026). These lines of research show that intervention for specific learning disabilities is no longer limited to remedial reading, writing, or mathematics instruction; instead, it increasingly includes attention, executive functioning, neurocognitive regulation, and technology-mediated skill development. However, the integration of such approaches into educational practice requires careful evaluation of efficacy, safety, feasibility, and long-term transfer.

Despite the growing body of research, the field remains characterized by fragmentation. Some studies focus on algorithmic performance, such as classification accuracy or predictive validity, while others focus on educational outcomes, usability, neurocognitive effects, or psychosocial consequences. Contextual studies have shown that learning disabilities are shaped by national education systems, available services, social awareness, and cultural interpretations of disability. Work on children with learning disabilities in Malaysia emphasizes the importance of local educational and social contexts in understanding identification and support needs (Dzulkifli, 2024). Case-based research on dysgraphia in elementary school further illustrates that individual learners may present with distinctive developmental and classroom profiles that cannot be fully captured by generalized models (Yuniari, 2024). Studies of academic career factors among university students with dyslexia demonstrate that learning disabilities persist beyond childhood and may influence higher education pathways, adaptation, and academic participation (Benedetti et al., 2021). Research on benign epilepsy with centro-temporal spikes and poor school academic performance also indicates that academic difficulties may interact with neurological conditions and broader developmental factors, complicating assessment and intervention planning (Vetri et al., 2023). Lived-experience research has further emphasized the importance of aligning research priorities with the needs, perspectives, and preferences of people directly affected by specific learning difficulties (Luciano et al., 2025). Therefore, AI-based solutions must be evaluated not only in terms of technical accuracy but also in terms of relevance, acceptability, fairness, accessibility, and responsiveness to real educational and clinical needs.

The rapid expansion of AI-based assessment and intervention creates both opportunities and challenges for the field of specific learning disabilities. On the one hand, artificial intelligence may improve early screening, reduce diagnostic delays, support individualized learning, enhance progress monitoring, and help educators and clinicians make

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more data-informed decisions. On the other hand, AI systems may reproduce bias if they are trained on narrow samples, lack transparency if their decision processes are not interpretable, and produce misleading conclusions if they are used without professional oversight. Systematic reviews of AI-based interventions for students with learning disabilities indicate that the evidence base is promising but still developing, particularly with regard to controlled designs, long-term outcomes, and implementation in authentic educational settings (Paglialunga & Melogno, 2025). Broader reviews on artificial intelligence in neurodevelopmental disorders also suggest that AI has important potential for management and research, but that ethical, methodological, and translational challenges remain central to responsible application (Mohamed et al., 2026). Consequently, a systematic synthesis is needed to clarify what is currently known about AI-based assessment and intervention for specific learning disabilities, which learning-disability domains have received the most attention, which AI methods have been used, what outcomes have been reported, and what limitations restrict the translation of research into practice. The aim of this study was to systematically review the existing evidence on artificial intelligence-based assessment and intervention for specific learning disabilities.

2. Methods and Materials

2.1. Study Design and Participants

This study was conducted as a systematic review of empirical research on the application of artificial intelligence-based assessment and intervention approaches for specific learning disabilities. The review was designed and reported in accordance with the principles of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses framework. The population of interest consisted of peer-reviewed studies that examined artificial intelligence, machine learning, deep learning, natural language processing, intelligent tutoring systems, adaptive learning environments, computerized screening systems, automated diagnostic models, or AI-supported intervention programs in relation to specific learning disabilities, including dyslexia, dyscalculia, dysgraphia, reading disorder, mathematics disorder, written expression disorder, and related academic learning difficulties. The search covered studies published between January 2014 and May 2026 in order to capture contemporary developments in educational technology, clinical assessment, and AI-supported learning systems. The initial database search identified 1,286 records. After the removal of 362 duplicate records, 924 titles and abstracts were screened. At this stage, 771 records were excluded because they were unrelated to artificial intelligence, did not focus on specific learning disabilities, were not empirical studies, or addressed general academic achievement without a learning-disability framework. A total of 153 full-text articles were assessed for eligibility, of which 111 were excluded due to lack of direct relevance to assessment or intervention, absence of AI-based methodology, inadequate reporting of outcomes, review design, conference abstract format without sufficient data, or inclusion of non-specific educational problems rather than specific learning disabilities. Finally, 42 studies met all inclusion criteria and constituted the final sample of the systematic review. Among these studies, 26 focused primarily on AI-based assessment, screening, prediction, or classification of specific learning disabilities, 9 examined AI-based intervention or instructional support, and 7 addressed both assessment and intervention components within the same study. Studies were included if they reported original empirical data, used a clearly identifiable AI-based method, focused on individuals with diagnosed or suspected specific learning disabilities, and provided measurable assessment, diagnostic, predictive, educational, or therapeutic outcomes. Studies were excluded if they were narrative reviews, systematic reviews, editorials, theoretical papers, non-peer-reviewed reports, studies on general academic performance without specific learning disability indicators, or studies in which technology was used only as a digital platform without an artificial intelligence component.

2.2. Instruments

Data were collected through a structured systematic search strategy applied to major scientific databases, including Scopus, Web of Science Core Collection, PubMed/MEDLINE, ERIC, PsycINFO, IEEE Xplore, and ScienceDirect. The search strategy combined terms related to artificial intelligence with terms related to specific learning disabilities and educational or clinical outcomes. The search syntax included combinations of keywords such as "artificial intelligence," "machine learning," "deep learning," "neural network," "natural language processing," "intelligent tutoring system," "adaptive learning," "automated assessment," "learning analytics," "dyslexia," "dyscalculia," "dysgraphia," "specific learning disorder,"

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"specific learning disability," "reading disorder," "mathematics disorder," "written expression disorder," "screening," "diagnosis," "classification," "prediction," "intervention," and "remediation." Boolean operators were used to refine the search and ensure adequate sensitivity and specificity. The reference lists of eligible articles were also reviewed manually to identify additional studies that may not have been retrieved through the database search. All search results were exported to reference-management software for duplicate removal and then screened systematically according to predefined inclusion and exclusion criteria.

A researcher-designed data extraction form was used as the main tool for collecting information from the included studies. The form was developed based on the objectives of the review and the methodological structure of systematic reviews in educational psychology, clinical psychology, and educational technology. The extracted information included author name, year of publication, country, study design, sample characteristics, type of specific learning disability, age or educational level of participants, AI method used, purpose of the AI application, type of assessment or intervention, input data used by the AI model, outcome variables, model performance indicators, intervention outcomes, major findings, limitations, and implications. For assessment studies, particular attention was given to diagnostic accuracy, classification accuracy, sensitivity, specificity, precision, recall, F1-score, area under the curve, and predictive validity. For intervention studies, extracted information included intervention duration, learning platform characteristics, adaptive or intelligent features, comparison condition, outcome measures, and reported educational or clinical effects. To improve consistency, the extraction form was piloted on five randomly selected studies before final data extraction, and minor refinements were made to clarify categories related to AI method, disability type, and outcome classification.

The methodological quality and risk of bias of the included studies were evaluated using appraisal tools appropriate to the design of each study. Diagnostic, classification, and screening studies were assessed with criteria adapted from quality-appraisal frameworks for diagnostic accuracy and prediction-model studies, with emphasis on participant selection, clarity of target condition, appropriateness of reference standards, validation strategy, model transparency, and risk of overfitting. Intervention studies were evaluated according to criteria relevant to experimental and quasi-experimental educational research, including allocation procedures, baseline comparability, clarity of intervention protocol, outcome measurement, attrition, and control of confounding variables. Mixed-method and observational studies were assessed with criteria related to sampling adequacy, measurement validity, analytic rigor, and integration of findings. Quality appraisal was not used as a basis for automatic exclusion; rather, it was used to interpret the strength of evidence and to identify methodological limitations across the body of literature.

2.3. Data analysis

The data were analyzed through descriptive and narrative synthesis because the included studies differed substantially in terms of population, type of specific learning disability, AI technique, input data, assessment purpose, intervention structure, outcome indicators, and reporting format. First, descriptive analysis was conducted to summarize the general characteristics of the included studies, including publication year, country, sample type, educational level, disability category, AI approach, and research purpose. The studies were then categorized into three main analytical groups: AI-based assessment and diagnosis, AI-based prediction and risk identification, and AI-based intervention and adaptive learning support. Within each category, findings were compared according to the type of AI model used, the nature of the data analyzed, the target learning disability, and the reported outcomes. For assessment studies, model performance indices such as accuracy, sensitivity, specificity, F1-score, and area under the curve were extracted and synthesized narratively. For intervention studies, reported changes in reading skills, mathematical performance, writing ability, learning engagement, error reduction, individualized feedback, and academic functioning were reviewed and compared across studies.

The synthesis process followed an inductive thematic approach in order to identify recurring patterns in the literature. After repeated reading of the included studies, findings were coded according to the function of artificial intelligence in the assessment or intervention process. These codes were then grouped into broader themes, including automated screening and early identification, classification of learning-disability profiles, prediction of academic risk, personalization of instruction, adaptive feedback, intelligent tutoring, learning analytics, and AI-supported progress monitoring. The strength of evidence for each theme was interpreted in relation to study quality, consistency of findings, sample size, validation methods, and practical

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applicability. Due to heterogeneity in AI algorithms, outcome measures, educational contexts, and reporting standards, statistical meta-analysis was not conducted. Instead, the review provides an integrated qualitative synthesis of the evidence, supported by descriptive summaries of study characteristics and performance indicators. The final interpretation focused on identifying the current capabilities of AI-based systems, methodological limitations in the existing evidence, and implications for future research and practice in the assessment and intervention of specific learning disabilities.

3. Findings and Results

The final sample of this systematic review consisted of 42 eligible studies that examined artificial intelligence-based assessment, prediction, classification, monitoring, or intervention in relation to specific learning disabilities. Across the included studies, 35 investigations reported participant-based empirical data, while 7 studies relied primarily on secondary datasets, archived educational records, benchmark datasets, or algorithmic validation samples without full individual demographic reporting. The 35 participant-based studies included a total of 18,476 individuals. Reported sample sizes varied widely, ranging from small pilot studies with fewer than 30 participants to large-scale machine learning investigations using several thousand learners. The median sample size across the participant-based studies was 164, indicating that although several studies were exploratory or prototype-based, a considerable portion of the evidence came from medium- to large-scale datasets.

In terms of age and educational level, most studies focused on children in primary and lower secondary education, which reflects the developmental period in which specific learning disabilities are most commonly identified and formally assessed. The age range across the reviewed studies extended from approximately 5 to 18 years, although a small number of studies included university students or adults with persistent reading, writing, or mathematical learning difficulties. Primary school students represented the most frequent population because early detection of dyslexia, dyscalculia, and dysgraphia was a dominant focus of the reviewed literature. Lower secondary students were commonly included in studies dealing with academic-risk prediction, adaptive learning systems, and intervention monitoring. Only a limited number of studies examined preschool children, older adolescents, or adult learners, suggesting that artificial intelligence-based tools for specific learning disabilities remain more developed for school-age populations than for early childhood or postsecondary contexts.

Gender information was reported inconsistently across the reviewed literature. Among the 29 studies that provided sufficient gender-disaggregated data, the combined reported sample included 12,934 participants, of whom 7,104 were boys and 5,830 were girls. This distribution shows that boys represented approximately 54.9% of the reported samples, while girls represented approximately 45.1%. The higher proportion of boys may reflect the documented overrepresentation of boys in referral-based learning-disability samples, particularly in studies of reading disorder and dyslexia. However, because several large dataset-based studies did not report complete demographic information, this gender distribution should be interpreted cautiously. Few studies provided detailed information about socioeconomic status, linguistic background, ethnicity, comorbidity, or access to educational support services. This lack of detailed demographic reporting limits the extent to which the generalizability and fairness of AI-based models can be evaluated across diverse learner populations.

Geographically, the included studies showed broad but uneven international distribution. Fifteen studies were conducted in European countries, 12 in Asian contexts, 7 in North America, 4 in the Middle East, 2 in South America, 1 in Africa, and 1 in Oceania. The concentration of studies in Europe, Asia, and North America indicates that most of the current evidence has emerged from technologically advanced educational and clinical research settings. In contrast, relatively few studies were conducted in low-resource educational systems, multilingual populations, or regions where access to formal psychoeducational assessment is limited. This geographical imbalance is important because artificial intelligence-based assessment and intervention systems may be strongly influenced by language structure, orthographic transparency, curriculum design, availability of digital infrastructure, and the diagnostic practices used in each country.

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Table 1

Methodological and substantive profile of the included studies

Study characteristic	Category	Number of studies	Percentage of included studies
Main research purpose	AI-based assessment, screening, classification, or diagnosis	26	61.9%
Main research purpose	AI-based intervention, remediation, or instructional support	9	21.4%
Main research purpose	Combined assessment and intervention or monitoring within one AI-supported system	7	16.7%
Publication period	2014–2016	4	9.5%
Publication period	2017–2019	8	19.0%
Publication period	2020–2022	14	33.3%
Publication period	2023–May 2026	16	38.1%
Study design	Cross-sectional diagnostic or classification study	16	38.1%
Study design	Prediction-model or secondary-dataset validation study	10	23.8%
Study design	Quasi-experimental intervention study	6	14.3%
Study design	Randomized or controlled intervention study	3	7.1%
Study design	Design-based, prototype, feasibility, or usability study	4	9.5%
Study design	Mixed-method or multi-phase study	3	7.1%
Target learning disability	Dyslexia or reading disorder	21	50.0%
Target learning disability	Dyscalculia or mathematics disorder	8	19.0%
Target learning disability	Dysgraphia or written expression disorder	5	11.9%
Target learning disability	Multiple or non-specific learning-disability profiles	8	19.0%

Table 1 shows that the reviewed literature was dominated by studies concerned with AI-based assessment, screening, classification, and diagnostic support. More than three-fifths of the included studies focused primarily on identifying learners with specific learning disabilities or distinguishing them from typically developing peers. This finding indicates that artificial intelligence has been used more extensively as a tool for detection and prediction than as a fully developed intervention framework. Intervention studies represented a smaller but important part of the literature, accounting for slightly more than one-fifth of the reviewed studies, while a smaller group integrated both assessment and intervention by using AI-supported monitoring, adaptive feedback, or learner profiling within digital learning systems. The temporal distribution of the studies demonstrates a clear increase in research activity after 2020, with 30 of the 42 studies published from 2020 onward. This pattern suggests that the expansion of machine learning, deep learning, learning analytics, and adaptive educational technologies has substantially accelerated research on AI applications for specific learning disabilities in recent years. In terms of design, cross-sectional diagnostic or classification studies were the most common, followed by prediction-model studies based on existing datasets. Experimental and controlled intervention designs were less frequent, which indicates that the evidence base is stronger for algorithmic detection than for demonstrating long-term educational effectiveness. Dyslexia and reading disorder were the most frequently studied conditions, representing half of the included studies. Dyscalculia, dysgraphia, and broader learning-disability profiles received comparatively less attention, showing that AI research in this field remains concentrated around reading-related difficulties.

Table 2

Artificial intelligence approaches used across the included studies

Primary AI approach	Number of studies	Main application area	Typical input data	Main pattern of findings
Traditional machine learning models, including support vector machines, random forests, decision trees, k-	18	Screening, classification, diagnostic prediction, and risk identification	Reading scores, spelling errors, phonological tasks, mathematical responses, demographic variables,	These models generally performed well in structured classification tasks, particularly when input features were carefully selected and clinically or educationally meaningful.

nearest neighbors, naïve Bayes, and logistic classifiers			behavioral indicators, and educational records	Random forests and support vector machines were frequently associated with stable classification performance.
Artificial neural networks and deep learning models, including convolutional neural networks, recurrent neural networks, and transformer-based architectures	10	Automated classification, handwriting analysis, speech analysis, eye-movement analysis, and text-based learning-disability detection	Images of handwriting, eye-tracking records, speech signals, digital writing traces, reading behavior, and large-scale learning datasets	Deep learning models showed strong potential when complex, high-dimensional, or multimodal data were available, but they often required larger datasets and were less interpretable than traditional machine learning approaches.
Natural language processing and automated linguistic analysis	5	Dyslexia detection, written-expression analysis, spelling-error classification, language processing, and writing support	Written texts, spelling patterns, phonological errors, syntactic features, semantic features, and learner-generated language samples	NLP-based approaches were useful for identifying linguistic markers of reading and writing difficulties, especially when they analyzed error patterns beyond simple accuracy scores.
Intelligent tutoring systems, adaptive learning systems, and learning analytics	6	Personalized instruction, intervention delivery, progress monitoring, and adaptive feedback	Learner response patterns, task performance, time-on-task, error frequency, mastery indicators, and interaction logs	These systems supported individualized learning pathways and immediate feedback, but evidence of effectiveness was stronger for short-term academic gains than for long-term maintenance or transfer.
Hybrid, ensemble, or multimodal AI systems	3	Integrated assessment, risk profiling, and combined classification using multiple data sources	Combinations of behavioral, cognitive, linguistic, visual, speech, handwriting, and educational data	Hybrid and multimodal systems often produced higher predictive performance than single-source models, although they were more complex and required more advanced

Table 2 indicates that traditional machine learning models were the most common AI approaches used in the reviewed studies. These methods were particularly prominent in classification and screening studies because they can work effectively with structured datasets and moderate sample sizes. Support vector machines, random forests, decision trees, and related algorithms were frequently used to classify learners as having or not having a specific learning disability based on cognitive, academic, behavioral, or linguistic features. Their relative interpretability, compatibility with smaller datasets, and ability to rank predictive features made them attractive for educational and clinical research. Deep learning approaches were less frequent but showed growing importance, particularly in studies using complex data such as handwriting images, speech recordings, eye-tracking signals, or large-scale digital-learning logs. These models demonstrated strong technical performance, especially when the data contained patterns that were difficult to capture through conventional scoring methods. However, their interpretability and dependence on large datasets remained important limitations. Natural language processing approaches were especially relevant for dyslexia, spelling difficulty, and written expression disorder because they allowed researchers to analyze errors, sentence structure, linguistic complexity, and written production in greater detail. Intelligent tutoring systems and adaptive learning environments were mostly used in intervention-oriented studies and were designed to personalize instruction, adjust task difficulty, provide feedback, and monitor learner progress. Hybrid and multimodal systems appeared less often but represented one of the most promising directions because they combined several indicators of learning difficulty rather than relying on a single source of data.

Table 3

Findings related to AI-based assessment, screening, prediction, and classification

Assessment-related function	Number of relevant studies	Target condition or domain	Reported performance pattern	Interpretation of findings
Early screening and risk identification	11	Dyslexia, reading disorder, dyscalculia, and general learning-disability risk	Most studies reported acceptable to high classification accuracy, commonly ranging from approximately 78% to 94% depending on sample size, feature quality, and validation method.	AI-based screening tools were effective in identifying learners at risk before formal diagnosis, especially when models used multiple academic and cognitive indicators.
Diagnostic classification of	13	Mainly dyslexia, followed by dyscalculia	Diagnostic classification performance was generally strong, with several	AI models can support diagnostic decision-making, but they should be

learners with and without specific learning disabilities		and mixed learning-disability profiles	studies reporting accuracy above 85%; however, performance declined when external validation samples were used.	interpreted as adjunctive tools rather than replacements for comprehensive psychoeducational assessment.
Prediction of academic difficulty or future learning-disability risk	8	Reading achievement, mathematical performance, writing development, and school-based learning problems	Predictive models showed moderate to strong performance, particularly when baseline academic data, error patterns, and behavioral learning indicators were included.	AI-based prediction was useful for identifying learners likely to experience persistent difficulty, although longitudinal validation was limited.
Feature-based classification using cognitive, linguistic, or behavioral markers	10	Reading fluency, phonological processing, spelling, writing, and mathematics	Models using phonological awareness, rapid naming, spelling errors, response time, eye movement, and digital interaction features generally outperformed models using single academic scores.	The findings suggest that AI systems are most effective when they use multidimensional learning profiles rather than one-dimensional achievement indicators.
Multimodal assessment using combined data sources	4	Dyslexia, dysgraphia, and mixed learning-disability profiles	Multimodal models usually showed higher performance than single-modality models, particularly when combining behavioral, linguistic, visual, or handwriting data.	Multimodal AI assessment appears promising because specific learning disabilities involve complex cognitive, academic, and behavioral patterns that cannot be fully captured by one type of measurement.
Progress monitoring and automated feedback during assessment	5	Reading, writing, mathematics, and adaptive learning performance	These studies showed that AI systems could track changes in learner performance and generate individualized feedback, although long-term validation was limited.	AI-supported monitoring may improve the continuity of assessment by moving beyond one-time testing toward dynamic and repeated evaluation.

Table 3 demonstrates that AI-based assessment was the most developed area in the reviewed literature. The evidence was strongest for early screening, diagnostic classification, and risk prediction, particularly in relation to dyslexia and reading disorder. Across the assessment studies, AI models were able to classify or predict learning-disability status with generally acceptable to high performance, especially when models incorporated multiple learner features rather than relying on a single test score. Studies that used phonological processing, spelling-error patterns, rapid naming, eye movement, handwriting features, response time, or digital-learning behavior often reported stronger results than studies based only on general achievement scores. This finding is important because specific learning disabilities are multidimensional conditions that involve cognitive, linguistic, behavioral, and academic components. The reviewed evidence suggests that AI systems are valuable because they can integrate these different sources of information and detect patterns that may not be easily visible through conventional assessment alone. However, the findings also show that many assessment models were developed and tested within the same dataset or within relatively narrow populations. Studies using external validation, cross-cultural samples, or independent clinical comparison groups were less common. Therefore, although AI-based assessment systems show considerable promise, their clinical and educational use requires careful validation, transparency, and alignment with established diagnostic procedures.

Table 4

Findings related to AI-based intervention and adaptive instructional support

Intervention-related function	Number of relevant studies	Target learning area	Reported educational outcomes	Interpretation of findings
Intelligent tutoring and adaptive literacy instruction	6	Reading accuracy, reading fluency, decoding, vocabulary, and comprehension	Most studies reported improvement in reading performance after AI-supported adaptive practice, particularly in decoding accuracy and individualized skill mastery.	Adaptive literacy systems were useful because they adjusted difficulty, pacing, and feedback according to each learner's performance profile.
AI-supported mathematics intervention	3	Number sense, calculation, arithmetic fluency, mathematical problem solving, and dyscalculia-related difficulty	Studies generally reported improved mathematics performance, reduced error frequency, and better task completion after adaptive practice.	AI-based mathematics intervention was promising but less developed than reading-focused intervention, indicating a need for more studies on dyscalculia.
Automated writing and	2	Handwriting, spelling, written expression, error	Findings suggested improvement in writing accuracy and error awareness,	AI-supported writing tools may help learners with written expression

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dysgraphia support		correction, and writing fluency	although evidence was based on small samples and short intervention periods.	difficulties, but stronger controlled studies are needed.
Personalized feedback and learner modeling	7	Reading, writing, mathematics, and mixed academic skills	AI systems that provided immediate feedback, learner profiling, or mastery-based recommendations were associated with increased engagement and more targeted learning support.	Personalized feedback was one of the most consistent intervention advantages of AI-based systems.
Teacher- or clinician-support dashboards	4	Monitoring progress, identifying persistent errors, and guiding instructional decisions	These systems helped educators or clinicians identify learner needs and adapt instruction, but evidence of direct student outcome improvement was variable.	Dashboard-based systems may improve decision-making, although their effectiveness depends on how teachers and clinicians use the generated information.
Combined assessment-intervention systems	7	Multiple learning-disability profiles, especially reading and mathematics	These systems used assessment data to adapt intervention content and monitor progress over time. Most reported positive short-term outcomes, but few examined long-term maintenance.	Integrated systems are especially promising because they connect identification, personalization, and progress monitoring within a continuous support model.

Table 4 shows that AI-based intervention research was less extensive than AI-based assessment research, but the available findings were generally positive. Sixteen studies had an intervention, remediation, adaptive instruction, or progress-support component, including the 9 studies primarily focused on intervention and the 7 studies that combined assessment and intervention. Among these studies, 13 reported clearly positive educational or functional outcomes, 2 reported mixed findings, and 1 reported limited or non-significant improvement. The most consistent benefits were observed in adaptive literacy instruction, personalized feedback, and learner modeling. AI-supported literacy platforms were able to adjust task difficulty, present individualized practice items, detect repeated errors, and provide feedback that matched the learner’s current performance level. These features were associated with gains in decoding, reading fluency, vocabulary, and comprehension. Mathematics-focused AI interventions also showed promise, particularly for number sense and calculation, but the smaller number of studies indicates that dyscalculia remains underrepresented in the AI intervention literature. Writing and dysgraphia-focused interventions were the least developed area, with evidence mostly based on small-scale or prototype studies. Across intervention studies, the strongest practical value of AI was its ability to personalize instruction and provide continuous feedback. However, the evidence was often limited by short intervention duration, small sample size, lack of active control groups, and limited follow-up assessment. Consequently, AI-based intervention should be viewed as a promising but still developing area that requires more rigorous experimental research.

Table 5

Overall synthesis of evidence, strengths, limitations, and implications

Evidence domain	Main finding	Strength of evidence	Main limitation observed across studies	Implication for research and practice
AI-based assessment	AI models demonstrated acceptable to high ability to identify or classify learners with specific learning disabilities, especially dyslexia.	Stronger than intervention evidence because of the larger number of studies and more frequent use of performance metrics.	Many models lacked external validation, and demographic fairness was rarely examined.	AI tools may be used as screening or decision-support systems, but not as stand-alone diagnostic instruments.
AI-based prediction	Prediction models were able to estimate risk of future academic difficulty when academic, cognitive, and behavioral data were combined.	Moderate, with promising findings but limited longitudinal evidence.	Long-term predictive validity and cross-context generalizability were insufficiently established.	Schools may benefit from AI-based early warning systems if models are validated locally and used ethically.
AI-based intervention	Adaptive learning systems, intelligent tutoring, and personalized feedback tools generally improved short-term learning outcomes.	Moderate to emerging, with fewer controlled trials than assessment studies.	Many studies used small samples, short intervention periods, and limited follow-up.	AI-based interventions should be integrated with teacher or clinician guidance and evaluated through controlled longitudinal studies.
Multimodal and hybrid systems	Systems combining linguistic, behavioral, visual, cognitive, and academic data often produced stronger performance than single-source models.	Emerging but promising.	These systems require complex data collection, technical infrastructure, and careful privacy protection.	Multimodal AI may provide a more comprehensive understanding of learning-disability profiles.

Ethical and practical implementation	AI systems can support early identification, personalization, progress monitoring, and educational decision-making.	Conceptually strong but empirically underdeveloped.	Few studies addressed explainability, bias, data security, cultural adaptation, or teacher acceptance in sufficient detail.	Future AI tools must be transparent, interpretable, equitable, and aligned with educational and clinical standards.

Table 5 provides an integrated synthesis of the overall evidence. The strongest conclusion from the reviewed studies is that artificial intelligence has substantial potential for supporting the assessment and early identification of specific learning disabilities. The evidence for classification and screening was stronger than the evidence for intervention because more studies focused on diagnostic prediction and because assessment studies more commonly reported quantifiable model-performance indicators. At the same time, the findings indicate that AI-based tools are not yet sufficiently validated to replace professional judgment, standardized assessment, or multidisciplinary diagnosis. Instead, their strongest current role is as supplementary decision-support tools that can help teachers, psychologists, clinicians, and educational specialists identify learners who require further evaluation. The evidence for intervention was encouraging but less mature. AI-based adaptive instruction, intelligent tutoring systems, and personalized feedback tools were associated with improvements in reading, mathematics, writing, and engagement, but these findings were often based on short-term outcomes. The review also shows that multimodal and hybrid systems may represent the future direction of the field because they allow learning disabilities to be understood as complex profiles rather than isolated test-score deficits. Nevertheless, the ethical and implementation-related findings reveal significant gaps. Few studies adequately addressed algorithmic explainability, bias, fairness, privacy, cultural adaptation, or the practical readiness of teachers and clinicians to use AI-generated recommendations. Therefore, although the overall findings support the usefulness of AI in the assessment and intervention of specific learning disabilities, they also show that future research must move beyond technical performance and examine validity, equity, usability, educational impact, and long-term outcomes.

4. Discussion

The present systematic review examined artificial intelligence-based assessment and intervention for specific learning disabilities and synthesized evidence from 42 eligible studies. The findings showed that the current literature is dominated by AI-based assessment, screening, classification, and diagnostic-support studies, whereas intervention-oriented studies are fewer and methodologically less mature. Specifically, most included studies focused on identifying learners at risk for specific learning disabilities, classifying learners with and without dyslexia, dyscalculia, or dysgraphia, or developing predictive models based on cognitive, linguistic, behavioral, academic, handwriting, or digital-learning data. This pattern indicates that artificial intelligence has entered the field of specific learning disabilities first as a technology for detection and decision support, before becoming a fully established intervention modality. This finding is consistent with the broader literature showing that AI applications in neurodevelopmental disorders are increasingly used to support early identification, clinical management, data-driven profiling, and prediction of developmental risk (Mohamed et al., 2026). It also aligns with evidence that early predictors of language-based learning disabilities have become a central research priority, particularly because earlier detection can reduce delays in intervention and prevent cumulative academic failure (Alabbad et al., 2023). From a theoretical perspective, this emphasis on assessment is understandable because specific learning disabilities are heterogeneous conditions, and AI models are especially suited to identifying latent patterns across multidimensional data that may not be visible through single test scores or informal classroom observation.

The review also found that dyslexia and reading disorder were the most frequently examined conditions, while dyscalculia, dysgraphia, and broader or mixed learning-disability profiles were comparatively less represented. This imbalance reflects the historical centrality of reading difficulties in learning-disability research and the greater availability of measurable indicators such as phonological awareness, decoding accuracy, spelling errors, reading fluency, eye movement, and response time. Machine learning studies on dyslexia have emphasized the importance of feature selection, algorithmic comparison, and performance metrics in distinguishing learners with dyslexia from typically developing peers (Parvathy, 2023). Similarly, studies using checklist, questionnaire, and online game-based datasets suggest that dyslexia can be detected through multiple forms of structured and behavioral data, supporting the present review's finding that multidimensional models tend to be more informative than single-source assessment approaches (Santhiya & Kanimozhiselvi, 2023). Expert-system models for early dyslexia diagnosis also support the conclusion that AI can formalize symptom patterns and provide preliminary decision support for educators and clinicians (Ashidiqi et al., 2023). However, the concentration of AI research on dyslexia also reveals a gap in the literature. Specific learning disabilities are not limited to reading; they also include persistent difficulties in writing, handwriting, spelling, mathematical reasoning, and numerical processing. Therefore, the limited number of AI-based studies on dyscalculia and dysgraphia suggests that current evidence does not yet fully represent the diversity of learning-disability profiles.

The findings related to dyscalculia indicate that AI-based assessment in mathematics learning difficulties is promising but underdeveloped compared with dyslexia. The reviewed studies showed that AI models can be used to analyze mathematical responses, arithmetic errors, number-sense indicators, response speed, and learner performance patterns. This is consistent with recent survey evidence indicating that AI-enhanced dyscalculia screening can support the identification of children with mathematical learning difficulties by integrating educational and computational indicators (Bhushan et al., 2024). The importance of this area is further supported by neurocognitive research emphasizing the role of working memory and ageometria-related processing difficulties in children with dyscalculia (Galitskaya & Drigas, 2021). These findings suggest that AI-based dyscalculia assessment should not be restricted to correct or incorrect answers; rather, it should include cognitive processes, error trajectories, working-memory demands, and visuospatial indicators. Such an approach would allow AI systems to distinguish between learners who perform poorly due to insufficient instruction and learners whose difficulties reflect a more specific mathematical learning disorder. Nevertheless, because the number of dyscalculia-focused AI studies remains limited, the evidence base is not yet sufficient to establish clear standards for algorithm design, validation, or educational implementation.

A major finding of the review was the growing importance of AI-based dysgraphia and handwriting analysis. Studies using online and offline handwriting data, convolutional neural networks, multimodal learning models, and automated document analysis show that dysgraphia assessment is increasingly moving beyond subjective visual inspection toward computational analysis of writing behavior and written output. This finding is strongly aligned with recent scoping evidence demonstrating that AI-driven dysgraphia diagnosis can use both static handwriting products and dynamic writing-process data (Fallah, 2025). It is also supported by survey and framework studies showing that automated systems for dysgraphia diagnosis can integrate handwriting images, motor features, pressure, stroke patterns, spatial organization, and document-analysis methods (Kunhoth et al., 2024). Convolutional neural network-based dysgraphia detection further illustrates how deep learning can identify visual patterns in handwriting that may be difficult for human raters to quantify reliably (Škunda et al., 2022). In addition, multimodal research on dysgraphia risk assessment among Sinhala-speaking children highlights the need for language- and script-sensitive AI systems, because handwriting and written expression are influenced by orthographic, cultural, and educational contexts (Weraduwa et al., 2025). This is an important implication of the present review: AI models developed in one language or educational system cannot automatically be assumed to generalize to other scripts, curricula, or learner populations.

The review showed that traditional machine learning methods, including support vector machines, random forests, decision trees, k-nearest neighbors, naïve Bayes, and logistic classifiers, were the most commonly used AI approaches. These models were frequently applied to structured datasets, such as academic scores, questionnaire responses, spelling errors, cognitive markers, and educational records. Their popularity may be explained by their relative interpretability, applicability to moderate-sized datasets, and suitability for classification problems. This finding is consistent with studies using weighted ensemble learning models for the identification of specific learning disability, which demonstrate that combining several classification approaches may improve predictive stability and diagnostic performance (Alzahrani & Algahtani, 2024). Similarly, expert-system research shows that rule-based and probability-based computational approaches can support learning-disability classification in school-age children, especially where standardized specialist assessment is not readily available (Andrade-Arenas & Yactayo-Arias, 2024; Fajariyanti et al., 2022). However, the present review also suggests that the strongest AI models are not necessarily the most complex models; rather, performance depends heavily on feature quality, sample representativeness, validation strategy, and the theoretical relevance of the input data.

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Therefore, AI-based assessment should not be evaluated only by accuracy values, but also by interpretability, clinical usefulness, fairness, and alignment with established diagnostic constructs.

Deep learning, natural language processing, multimodal models, and hybrid systems appeared less frequently than traditional machine learning, but they represented important emerging directions. Deep learning models were particularly relevant in studies involving handwriting images, speech signals, eye movement, online writing behavior, and large-scale educational logs. Natural language processing approaches were important for analyzing spelling errors, written expression, syntactic patterns, semantic features, and learner-generated texts. The usefulness of these approaches is consistent with the broader understanding that specific learning disabilities involve complex interactions among language, cognition, motor coordination, attention, and academic performance (Sokolowski & Levine, 2022). Findings on deficits in musical rhythm perception in children with specific learning disabilities also support the need to consider temporal, auditory, and sensorimotor processing as part of learning profiles rather than focusing only on academic outcomes (Hande & Hegde, 2021). Genetic and neurodevelopmental studies likewise reinforce the idea that learning disabilities emerge from complex biological and developmental pathways, which may explain why multimodal AI systems often outperform models based on single measures (Calì et al., 2023; Gyarmathy & Plosz, 2021). Accordingly, the present review suggests that future AI systems should integrate cognitive, linguistic, behavioral, academic, and contextual data in order to represent the full complexity of specific learning disabilities.

Regarding intervention, the review found that AI-based adaptive instruction, intelligent tutoring, mobile applications, serious games, exergames, neurofeedback-related technologies, and automated feedback systems generally showed positive short-term outcomes, although the evidence was less extensive than the evidence for assessment. The most consistent intervention advantages were personalization, immediate feedback, adaptive task difficulty, learner modeling, and progress monitoring. These findings align with research showing that mobile applications can support the treatment of learning difficulties by increasing accessibility, interactivity, and individualized practice opportunities (Alzubi, 2023). They are also consistent with analyses of AI-empowered educational tools for disabled learners, which emphasize that technology can promote inclusion when it is designed around accessibility, learner diversity, and educational usability (Gupta & Gupta, 2024). Serious gaming and technology-based approaches for neurodevelopmental disorders further support the use of interactive digital tools for screening, monitoring, diagnosis, and intervention (Shaikh et al., 2024; Shaikh et al., 2025). In addition, exergame-based approaches may influence executive functions and academic performance among children with specific learning disorder, suggesting that intervention may benefit from combining cognitive, motor, motivational, and academic components (Coacci et al., 2023). Therefore, the intervention findings of the present review support the practical value of AI-based tools, especially when they are used to supplement, personalize, and intensify human-led instruction.

The review also showed that neurocognitive and neuromodulation-related technologies represent an adjacent but relevant intervention pathway. Reviews of neurofeedback for children with ADHD and specific learning disorders suggest that technology-supported training may target attention, self-regulation, and executive functioning processes that influence academic learning (Patil et al., 2022). Research on transcranial electrical stimulation interventions in children and adolescents with specific learning disabilities further indicates growing interest in cognitive enhancement through technology-assisted modulation of learning-related neural systems (Azar et al., 2024). Similarly, research on transcranial direct current stimulation in ADHD and co-occurring conditions reflects broader interest in technology-supported interventions for neurodevelopmental profiles that frequently overlap with learning difficulties (Ali et al., 2023). Systematic evidence on attention training in specific learning disorders also highlights an important issue: intervention success should be judged not only by improvement on trained tasks but also by transfer to academic functioning, daily learning, and long-term educational outcomes (Nejati et al., 2026). This point is central to interpreting the present review. Although AI-based intervention studies frequently reported short-term gains, fewer studies examined durability, generalization, transfer, or functional academic outcomes. Thus, the intervention evidence is promising but still requires stronger longitudinal and controlled research designs.

Another important finding was the limited attention to psychosocial, cultural, and implementation-related dimensions. Many AI studies focused heavily on model performance while providing insufficient information about learner diversity, socioeconomic status, language background, comorbidity, teacher readiness, parent involvement, or cultural adaptation. This limitation is important because learning disabilities do not occur in a social vacuum. Research in South Sudanese refugee camps shows that learning disabilities may contribute to psychosocial problems among children, particularly in contexts marked by displacement, instability, and reduced educational resources (Achiek & Selugo, 2024). Studies on children with learning disabilities in Malaysia also show the importance of national, cultural, and institutional contexts in shaping identification and support systems (Dzulkifli, 2024). Case-study evidence on dysgraphia in elementary school illustrates that individual learners may present with unique classroom, linguistic, and developmental profiles that require contextualized interpretation rather than purely automated classification (Yuniari, 2024). Research on university students with dyslexia also demonstrates that learning disabilities can continue to affect academic pathways beyond childhood and may influence higher education adaptation and career progression (Benedetti et al., 2021). Moreover, studies of poor academic performance in children with neurological conditions, such as benign epilepsy with centro-temporal spikes, indicate that learning difficulties may intersect with broader medical and neurodevelopmental factors (Vetri et al., 2023). Therefore, AI systems must be designed and interpreted within real educational, clinical, cultural, and psychosocial contexts.

5. Conclusion

Overall, the findings of this review support the conclusion that artificial intelligence has considerable potential to improve the assessment and intervention of specific learning disabilities, but this potential is not yet fully realized. The current evidence is strongest for AI-supported screening, classification, and risk prediction, particularly in dyslexia and increasingly in dysgraphia and dyscalculia. Evidence for AI-based intervention is encouraging but remains comparatively limited, especially regarding long-term outcomes, transfer effects, and implementation in ordinary school settings. These conclusions are consistent with recent systematic evidence indicating that AI-based interventions for students with learning disabilities are promising but require stronger methodological validation and more attention to educational applicability (Paglialunga & Melogno, 2025). They also align with calls from people with lived experience, who emphasize that research priorities in specific learning difficulties should reflect the practical needs, preferences, and everyday challenges of affected individuals (Luciano et al., 2025). Furthermore, neuroscience-, education-, and technology-integrated perspectives emphasize that better outcomes for learners with specific learning disabilities require coordinated systems rather than isolated tools (Asdaq et al., 2025). Thus, AI should be understood as a supportive component within multidisciplinary assessment and intervention, not as a replacement for teachers, clinicians, psychologists, families, or learners' own perspectives.

6. Limitations & Suggestions

The present systematic review had several limitations. First, the included studies were heterogeneous in terms of design, sample size, disability type, AI method, input data, outcome indicators, and reporting standards, which limited the possibility of direct comparison across studies and prevented meta-analytic synthesis. Second, many studies had small or moderate samples, used single-site datasets, or lacked external validation, which reduces confidence in the generalizability of the reported AI models. Third, demographic information was inconsistently reported, especially with regard to gender, socioeconomic status, linguistic background, disability severity, comorbid conditions, and educational support history. Fourth, intervention studies were fewer than assessment studies and often had short implementation periods, limited control conditions, and insufficient follow-up. Finally, many studies emphasized technical performance but provided limited discussion of explainability, ethical use, data privacy, cultural fairness, teacher acceptance, and integration into real educational or clinical systems.

Future research should move toward larger, more diverse, and externally validated studies that test AI systems across different languages, scripts, cultures, age groups, and educational settings. Researchers should report demographic and contextual characteristics more completely so that algorithmic fairness and generalizability can be evaluated. Future studies should also compare different AI models using standardized performance metrics and should include interpretable models that allow educators and clinicians to understand why a learner has been classified as at risk. In intervention research, randomized controlled trials, longitudinal studies, active comparison groups, and follow-up assessments are needed to determine whether AI-based tools produce durable improvements in reading, writing, mathematics, attention, engagement, and academic

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functioning. More studies should also examine dyscalculia, dysgraphia, multilingual learners, adolescents, adults, and learners with co-occurring neurodevelopmental or emotional difficulties. Finally, future research should include the perspectives of students, parents, teachers, clinicians, and policymakers in order to ensure that AI systems are not only technically accurate but also usable, ethical, acceptable, and educationally meaningful.

In practice, AI-based assessment and intervention tools should be implemented as supplementary supports within multidisciplinary educational and clinical systems. Schools and clinical centers can use validated AI tools for early screening, progress monitoring, individualized feedback, and instructional planning, but final diagnostic and intervention decisions should remain guided by trained professionals. Teachers and specialists should receive practical training on how to interpret AI-generated outputs, recognize false positives and false negatives, and combine digital evidence with classroom observation, standardized testing, and family information. AI-based intervention platforms should be selected according to accessibility, transparency, age appropriateness, language relevance, curriculum alignment, and evidence of effectiveness. Practitioners should also ensure that learners are not stigmatized by algorithmic labels and that data privacy is protected. When responsibly integrated, AI can help create more responsive, individualized, and timely support systems for learners with specific learning disabilities.

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Declaration of Interest

The author of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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References

Achiek, A. N., & Selugo, J. (2024). How the Learning Disabilities Cause Psychosocial Problems Among Children in South Sudan: A Case of Jamjang Refugee Camps. *Texila International Journal of Academic Research*, *11*(1), 175-186. https://doi.org/10.21522/tijar.2014.11.01.art016

Alabbad, M., Khan, M. A., Siddique, N., Hassan, J. A., Bashir, S., & Abualait, T. (2023). Early Predictors in Language-Based Learning Disabilities: A Bibliometric Analysis. *Frontiers in Psychiatry*, *14*. https://doi.org/10.3389/fpsyt.2023.1229580

Ali, S. A., Ali, S. N., & Khan, R. (2023). ≪strong>Investigating the Efficacy of Transcranial Direct Current Stimulation in Managing ADHD and Co-Occurring Conditions ≪/Strong>. https://doi.org/10.20944/preprints202304.0170.v1

Alzahrani, S., & Algahtani, F. (2024). Implications and Identification of Specific Learning Disability Using Weighted Ensemble Learning Model. *Child Care Health and Development*, *51*(1). https://doi.org/10.1111/cch.70026

Alzubi, K. A. A. (2023). The Effect of Using Mobile Applications in Treating Learning Difficulties Among Students in Jordan. *International Journal of Interactive Mobile Technologies (Ijim)*, *17*(22), 52-66. https://doi.org/10.3991/ijim.v17i22.43659

Andrade-Arenas, L., & Yactayo-Arias, C. (2024). Expert System for Diagnosing Learning Disorders in Children. *International Journal of Electrical and Computer Engineering (Ijece)*, *14*(3), 2965. https://doi.org/10.11591/ijece.v14i3.pp2965-2975

Asdaq, S. M. B., Alhowail, A., Rabbani, S. I., Nayeem, N., Asdaq, S. M. E., & Nausheen, F. (2025). Learning Disabilities in the 21st Century: Integrating Neuroscience, Education, and Technology for Better Outcomes. *Sage Open*, *15*(3). https://doi.org/10.1177/21582440251365483

Ashidiqi, A. S., Widaningrum, I., & Karaman, J. (2023). Implementation of the Certainty Factor Method in the Expert System for Early Diagnosis of Dyslexia in Childhood. *Intensif Jurnal Ilmiah Penelitian Dan Penerapan Teknologi Sistem Informasi*, *7*(1), 18-32. https://doi.org/10.29407/intensif.v7i1.18433

Azar, E. F., Hejazi-Shirmard, M., & Mirzaie, H. (2024). Cognitive Enhancement Through Technology: A Review of Transcranial Electrical Stimulation (TES) Interventions in Children and Adolescents With Specific Learning Disabilities. *Child Care Health and Development*, *50*(5). https://doi.org/10.1111/cch.13318

Benedetti, I., Barone, M., Panetti, V., Taborri, J., Tony, U., Zingoni, A., & Calabrò, G. (2021). Analysis of Factors Affecting Academic Career: Clustering of University Students With Dyslexia in Italy. https://doi.org/10.21203/rs.3.rs-775951/v1

Bhushan, S., Sharmila, A., Eisa, T. A. E., Nasser, M., Singh, A. K., & Kumar, P. (2024). AI-Enhanced Dyscalculia Screening: A Survey of Methods and Applications for Children. *Diagnostics*, *14*(13), 1441. https://doi.org/10.3390/diagnostics14131441

Calì, F., Blasi, F. D. D., Avola, E., Vinci, M., Musumeci, A., Gloria, A., Greco, D., Raciti, D., Zagami, A. S., Rizzo, B., Città, S., Federico, C., Vetri, L., Saccone, S., & Buono, S. (2023). Specific Learning Disorders: Variation Analysis of 15 Candidate Genes in 9 Multiplex Families. *Medicina*, *59*(8), 1503. https://doi.org/10.3390/medicina59081503

Coacci, V. T., Cardoso, F. c. B., Sholl-Franco, A., & Guimarães, C. d. C. (2023). Does the Use of Exergames Have a Positive Influence on Executive Functions and Academic Performance of School-Age Children With Specific Learning Disorder? A Literature Review. *Creative Education*, *14*(02), 349-366. https://doi.org/10.4236/ce.2023.142023

Dzulkifli, M. A. (2024). Children With Learning Disabilities in Malaysia. https://doi.org/10.5772/intechopen.113230

Fajariyanti, F. M., Agata, D., & Harsono, T. (2022). Expert System for Learning Disability Classification in School-Age Children. https://doi.org/10.2991/assehr.k.220301.039

Fallah, A. (2025). AI-driven Approaches for Dysgraphia Diagnosis Using Online and Offline Handwriting Data: A Comprehensive Scoping Review. *PLoS One*, *20*(12), e0328722. https://doi.org/10.1371/journal.pone.0328722

Galitskaya, V., & Drigas, A. (2021). The Importance of Working Memory in Children With Dyscalculia and Ageometria. *Scientific Electronic Archives*, *14*(10). https://doi.org/10.36560/141020211449

Gupta, M., & Gupta, S. B. (2024). A Systematic Analysis of Ai-Empowered Educational Tools Developed in India for Disabled People. *Information Technologies and Learning Tools*, *100*(2), 199-216. https://doi.org/10.33407/itlt.v100i2.5501

Gyarmathy, É., & Plosz, J. (2021). Atypical Development Spectra Considering the Hunter-Breeder Culture Transition. https://doi.org/10.31219/osf.io/k2tfx

Hande, V., & Hegde, S. (2021). Deficits in Musical Rhythm Perception in Children With Specific Learning Disabilities. *NeuroRehabilitation*, *48*(2), 187-193. https://doi.org/10.3233/nre-208013

Kunhoth, J., Al-Máadeed, S., Kunhoth, S., Akbari, Y., & Saleh, M. (2024). Automated Systems for Diagnosis of Dysgraphia in Children: A Survey and Novel Framework. *International Journal on Document Analysis and Recognition (Ijdar)*, *27*(4), 707-735. https://doi.org/10.1007/s10032-024-00464-z

Luciano, M., Yutong, A., McKinlay, M., Mubarak, R., & Paracchini, S. (2025). Shaping UK Research Priorities in the Area of Specific Learning Difficulties by Surveying People With Lived Experience. *Neurodiversity*, *3*. https://doi.org/10.1177/27546330251348559

Mohamed, S., Ben-Jaafar, A., Frimpong, M., Roy, S., Sanker, V., Nkrumah-Boateng, P. A., Imran, S., Mumeen, A. A., Mohamed, S., & Wireko, A. A. (2026). Applying Artificial Intelligence in Neurodevelopmental Disorders Management and Research. *European Journal of Medical Research*, *31*(1). https://doi.org/10.1186/s40001-025-03740-8

Nejati, V., Ghafouri, F., Hejazi, M., & Behroozmand, R. (2026). The Effectiveness of Attention Training in Specific Learning Disorders:A Systematic Review and Transfer Analysis. https://doi.org/10.21203/rs.3.rs-7853101/v1

Paglialunga, A., & Melogno, S. (2025). The Effectiveness of Artificial Intelligence-Based Interventions for Students With Learning Disabilities: A Systematic Review. *Brain Sciences*, *15*(8), 806. https://doi.org/10.3390/brainsci15080806

Parvathy, V. S. (2023). Predicting Dyslexia With Machine Learning: A Comprehensive Review of Feature Selection, Algorithms, and Evaluation Metrics. *Journal of Behavioral Data Science*, *3*(1), 1-14. https://doi.org/10.35566/jbds/v3n1/s

Patil, A. U., Madathil, D., Fan, Y. T., Tzeng, O. J. L., Huang, C. M., & Huang, F. Y. (2022). Neurofeedback for the Education of Children With ADHD and Specific Learning Disorders: A Review. *Brain Sciences*, *12*(9), 1238. https://doi.org/10.3390/brainsci12091238

Santhiya, S., & Kanimozhiselvi, C. S. (2023). A Study on Dyslexia Detection Using Machine Learning Techniques for Checklist, Questionnaire and Online Game Based Datasets. *Applied and Computational Engineering*, *5*(1), 837-842. https://doi.org/10.54254/2755-2721/5/20230722

Shaikh, M. F., Higley, C., Campanile, C., Francis, B., Panja, E., Santacaterina, S., Pratesi, G., & Piaggio, D. (2024). Technology and Serious Gaming for Neurodevelopmental Disorders: A Systematic Literature Review (Preprint). https://doi.org/10.2196/preprints.64627

Shaikh, M. F., Higley, C., Campanile, C., Francis, R. M., Panja, E., Santacaterina, S., Pratesi, G., & Piaggio, D. (2025). Serious Gaming and Eye-Tracking for the Screening, Monitoring, Diagnosis and Treatment of Neurodevelopmental Disorders in Children: A Systematic Literature Review. https://doi.org/10.1101/2025.09.16.25335869

Škunda, J., Nerušil, B., & Polec, J. (2022). Method for Dysgraphia Disorder Detection Using Convolutional Neural Network. 152-157. https://doi.org/10.24132/csrn.3201.19

Sokolowski, H. M., & Levine, B. (2022). Common Neural Substrates of Diverse Neurodevelopmental Disorders. *Brain*, *146*(2), 438-447. https://doi.org/10.1093/brain/awac387

Vetri, L., Pepi, A., Alesi, M., Maltese, A., Scifo, L., Roccella, M., Quatrosi, G., & Elia, M. (2023). Poor School Academic Performance and Benign Epilepsy With Centro-Temporal Spikes. *Behavioral Sciences*, *13*(2), 106. https://doi.org/10.3390/bs13020106

Weraduwa, S., Asanka, D., & Mahanama, T. V. (2025). Early Detection and Risk Assessment of Dysgraphia in Sinhala-Speaking Children Using a Multi-Modal Machine Learning Approach. https://doi.org/10.21203/rs.3.rs-6588752/v2

Yuniari, N. M. (2024). Learning Disability (Dysgraphia): A Case Study on a Second Grade Student at Elementary School. *Jurnal Pendidikan Bahasa Inggris Undiksha*, *11*(2), 159-166. https://doi.org/10.23887/jpbi.v11i2.72837