

Artificial Intelligence in Special Education: A Review of Adaptive Learning Systems, Personalized Support, and Ethical Challenges for Learners with Disabilities

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ABSTRACT:

Artificial intelligence (AI) is increasingly entering special and inclusive education through adaptive learning platforms, intelligent tutoring systems, learning analytics, speech and language tools, computer vision, generative AI, and assistive technologies. For learners with disabilities, these systems can reduce barriers in curriculum access, communication, formative feedback, assessment participation, independence, and teacher workload. However, the evidence base remains uneven. Current reviews show stronger concentration on dyslexia, adaptive instruction, and selected intelligent tutoring applications, while comparatively fewer studies address dyscalculia, intellectual disability, complex communication needs, multiple disabilities, low-resource settings, long-term classroom implementation, or learner agency. This critical review synthesizes research and policy literature on AI in special education across three interlinked dimensions: adaptive learning systems, personalized support for diverse disability groups, and ethical governance. The review argues that AI should not be understood as a replacement for special educators, therapists, or individualized education planning. Its strongest role is as a carefully governed support layer that can improve diagnosis-informed instruction,

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multimodal access, formative feedback, communication, classroom decision-making, and inclusive participation. The paper contributes a disability-responsive AI architecture, a risk-to-governance matrix, and a practical adoption framework for schools. Responsible AI in special education must be accessible by design, pedagogically valid, disability-responsive, transparent, privacy-protective, bias-audited, teacher-supervised, and aligned with learner dignity and self-determination.

Keywords: artificial intelligence; special education; inclusive education; adaptive learning; intelligent tutoring systems; assistive technology; learners with disabilities; AI ethics; personalized learning; educational equity

1. Introduction

Special education has always required individualization. Learners with disabilities may differ not only in academic level but also in sensory access, communication mode, attention, executive functioning, motor ability, social interaction, processing speed, emotional regulation, and need for assistive support. Traditional classroom systems often struggle to provide continuous individualized feedback at the scale required for genuinely inclusive education. Artificial intelligence has therefore gained attention as a possible tool for designing adaptive learning environments, personalized scaffolding, automated feedback, accessible communication systems, early screening, and teacher decision support (Rose & Meyer, 2002; CAST, 2018; Alnahdi, 2014; Edyburn, 2005; Holmes et al., 2019; Luckin et al., 2016; Hwang et al., 2020; Chen et al., 2020; Chassignol et al., 2018).

The promise is significant, but the field must avoid technological optimism. UNESCO's guidance on AI and education frames AI as a policy, pedagogical, and ethical issue rather than merely a technological innovation; it emphasizes equitable and inclusive use, human capacity development, and governance for responsible educational adoption. UNESCO's guidance on generative AI similarly stresses that educational uses of AI require regulation, validation, privacy protection, and a human-centred vision. These cautions are particularly important in special education, where learners may generate sensitive educational, disability-related, behavioral,

speech, sensory, and biometric data. (UNESCO, 2021; UNESCO, 2023a; UNESCO, 2023b; UNESCO, 2025; OECD, 2024; Linsenmayer, 2025)

AI in special education must therefore be examined through a dual lens. First, it can support personalized access by adjusting content, pace, modality, feedback, and communication according to learner needs. Second, it can create new risks through algorithmic bias, surveillance, inaccurate classification, overdependence, exclusion of low-resource learners, weak data protection, and loss of human judgment. OECD's recent work on AI for students with special education needs highlights the same tension: AI may support access and learning goals, but risks and limitations require careful implementation and oversight. (Rice & Dunn, 2023; Paglialunga et al., 2025; Panjwani-Charania & Zhai, 2023; UNICEF, 2021; European Commission, 2022)

This review examines the current role of AI in special education with emphasis on adaptive learning systems, personalized support across disability categories, and ethical challenges. Rather than presenting AI as a single solution, it positions AI as a socio-technical system that must be aligned with disability rights, inclusive pedagogy, teacher expertise, evidence-based intervention, universal design, assistive technology principles, and strong governance.

2. Review Method and Scope

This manuscript follows a critical narrative review approach. It synthesizes peer-reviewed

articles, systematic reviews, international policy reports, and conceptual literature on AI in education, special education, inclusive education, learning disabilities, adaptive technologies, assistive technology, learning analytics, and AI ethics. Priority was given to sources that address learners with special educational needs and disabilities, responsible AI, educational technology governance, or evidence-based inclusive pedagogy. (Zawacki-Richter et al., 2019; Papamitsiou & Economides, 2014; Ferguson, 2012; Viberg et al., 2018)

The review was organized around five questions: (i) What types of AI systems are being applied in special education? (ii) How do adaptive learning systems personalize instruction for learners with disabilities? (iii) What forms of disability-specific support are currently most developed? (iv) What ethical, legal, pedagogical, and equity concerns arise? (v) What framework can guide responsible AI integration in special education?

The paper does not claim to estimate pooled effect sizes. The evidence base is heterogeneous in design, disability category, intervention type, outcome measure, setting, and duration. Panjwani-Charania and Zhai's systematic review of AI for students with learning disabilities, for example, included 16 studies and reported that 10 focused on dyslexia, only one on dyscalculia, and the remaining studies on learning disabilities in general; only half focused on school-age children. Such findings show promise, but also reveal the narrowness of the existing evidence base. (Panjwani-Charania & Zhai, 2023; Paglialunga et al., 2025; Rice & Dunn, 2023;

Perelmutter et al., 2017; Okolo & Diedrich, 2014)

3. Conceptual Foundation: What Counts as AI in Special Education?

AI in special education refers to computational systems that use data-driven or rule-based methods to perform functions usually associated with human judgment, such as recognizing learner performance patterns, adapting tasks, generating feedback, predicting difficulty, classifying errors, supporting communication, or recommending instructional pathways. These systems may include machine learning models, natural language processing, speech recognition, computer vision, recommender systems, intelligent tutoring systems, generative AI, and learning analytics. (Woolf, 2010; Roll & Wylie, 2016; Baker & Smith, 2019; Baker & Inventado, 2014; Siemens & Baker, 2012)

The most important distinction is between AI as access support and AI as decision authority. AI may assist teachers by generating accessible materials, tracking progress, providing practice opportunities, or transforming information into alternative modalities. However, decisions about disability identification, placement, high-stakes assessment, behavior interpretation, accommodations, or individualized education plans should remain under qualified human oversight. This teacher-in-the-loop position is consistent with the broader ethical literature that views AI in education as part of a human, social, and pedagogical system rather than a neutral technical tool. (Floridi & Cowls, 2019; Jobin et al., 2019; Mittelstadt et al., 2016)

Table 1. Major AI applications in special education and associated risks.

AI application	Core function	Special education relevance	Main risk
Intelligent tutoring systems	Stepwise instruction, hints, corrective feedback, mastery tracking	Supports individualized pacing and practice for learners needing repeated guided instruction	May not reflect disability-specific barriers or inclusive pedagogy
Adaptive learning platforms	Adjust difficulty, sequence, modality,	Useful for learners with dyslexia, dyscalculia,	Opaque adaptation may lower challenge or

AI application	Core function	Special education relevance	Main risk
	repetition, and feedback	ADHD, and variable processing speed	misinterpret access difficulty as low ability
Learning analytics	Detect patterns in performance, engagement, or risk	Helps teachers monitor progress and identify barriers earlier	Privacy, surveillance, and biased risk flags
Speech recognition and text-to-speech	Convert speech and text across modalities	Supports visual impairment, dyslexia, motor disability, and communication access	Poor accuracy for atypical speech, accents, noise, and multilingual learners
Computer vision	Detect gestures, written work, eye gaze, movement, or visual context	Potential support for navigation, handwriting, AAC, or motor assessment	Biometric privacy and misinterpretation of neurodivergent behavior
Generative AI	Create explanations, summaries, examples, quizzes, and alternative formats	Can adapt reading level, language, examples, and multimodal supports	Hallucination, bias, copyright issues, overreliance, and lack of validation
Social robots/conversational agents	Provide structured interaction, prompts, routines, and practice	Used in autism support, communication practice, and predictable routines	Risk of replacing authentic peer/adult interaction or normalizing narrow social behaviors
AI-assisted assessment	Automate screening, scoring, classification, or feedback	May support early identification and formative assessment	False positives, false negatives, labeling, and high-stakes misuse

4. Adaptive Learning Systems in Special Education

Adaptive learning systems are among the most relevant AI applications for special education because they can adjust instruction according to learner performance. In a conventional classroom, a teacher may provide differentiated instruction, but continuous micro-level adaptation for every learner is difficult. AI systems can potentially adjust reading difficulty, problem sequence, hints, feedback timing, repetition, modality, and mastery thresholds. However, disability-responsive adaptation requires more than correct-or-incorrect scoring. It requires attention to the difference between academic difficulty and access difficulty. (Aleven

et al., 2016; Anderson et al., 1995; Corbett & Anderson, 1995; Koedinger et al., 1997)

A learner with dyslexia may understand a concept but struggle with decoding text. A learner with cerebral palsy may know the answer but respond slowly because of motor constraints. A learner with autism may disengage due to sensory overload rather than lack of motivation. A learner with hearing impairment may miss a spoken instruction because the captioning was inaccurate. Therefore, adaptive AI must be designed to interpret learner performance through the lens of accessibility, disability, context, and teacher knowledge.

4.1 Architecture of Disability-Responsive Adaptive Learning

A disability-responsive adaptive learning system should include at least five layers: learner profile, multimodal data collection, AI interpretation, adaptation, and human oversight. The learner profile layer is especially important in special

education because it connects the AI tool with individualized goals, access modes, and documented supports. The human oversight layer prevents the system from becoming a hidden decision-maker. Figure 1 presents a conceptual architecture for responsible adaptive learning in special education.

Disability-Responsive AI Adaptive Learning Architecture

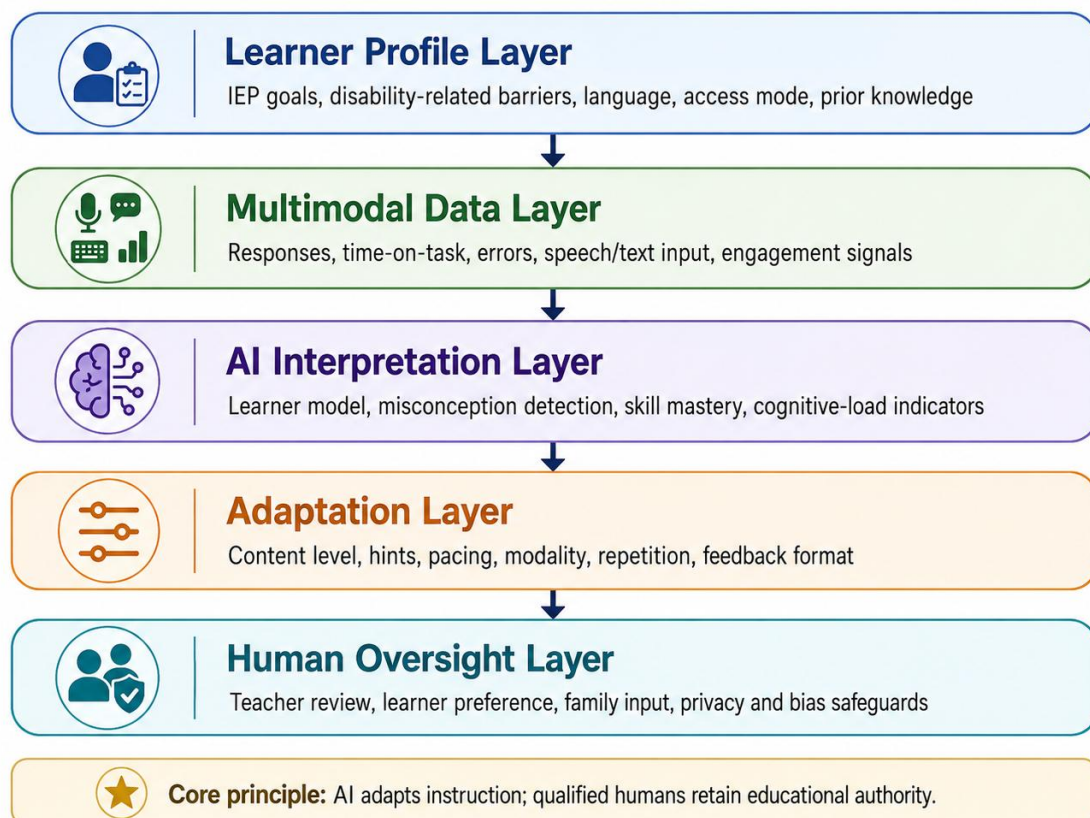


Figure 1. Disability-responsive AI adaptive learning architecture.

4.2 Adaptive Learning for Learning Disabilities

Learning disabilities are currently among the better represented areas in AI-special education literature, especially dyslexia. AI tools may support decoding, phonological awareness, reading fluency, spelling, grammar, writing organization, and comprehension through text-to-speech, speech-to-text, adaptive reading passages, error-pattern detection, and personalized practice. The available evidence, however, remains uneven. Panjwani-Charania and Zhai reported a strong concentration on dyslexia and limited attention to dyscalculia,

suggesting that the field is not yet balanced across learning disability profiles. (Adebisi et al., 2015; Drigas & Ioannidou, 2013; Drigas & Politi-Georgousi, 2019; Bouck & Flanagan, 2010; Perelmutter et al., 2017)

For dyslexia, AI-based systems can adapt text complexity, provide audio support, segment syllables, detect spelling errors, offer repeated reading practice, and reduce the social embarrassment associated with repeated mistakes. For dyscalculia, AI could support number sense, symbolic-magnitude mapping, arithmetic strategy feedback, visual manipulatives, and stepwise error diagnosis. Yet

dyscalculia has received much less attention than dyslexia, making it a clear gap for future research. (Shute, 2008; Kulik & Fletcher, 2016;

Ma et al., 2014; Steenbergen-Hu & Cooper, 2014; VanLehn, 2011)

Table 2. AI-supported adaptations for learners with learning disabilities.

Learning barrier	AI-supported adaptation	Educational value	Safeguard
Slow decoding	Text-to-speech, syllable segmentation, audio support	Reduces decoding burden during comprehension activities	Do not reduce conceptual challenge unnecessarily
Spelling difficulty	Error-pattern recognition and individualized spelling feedback	Targets repeated error types instead of generic correction	Feedback should be supportive and explainable
Working memory load	Chunked instructions, visual cues, stepwise prompts	Prevents overload and supports executive functioning	Avoid excessive prompts that reduce independence
Low reading fluency	Repeated reading with feedback and progress monitoring	Supports automaticity and confidence	Measure transfer to real reading tasks
Mathematical symbol confusion	Visual number lines, manipulatives, stepwise arithmetic feedback	Supports number sense and conceptual mapping	Validate specifically for dyscalculia
Writing organization difficulty	AI-assisted outlines, sentence starters, revision prompts	Supports planning and expression	Learner voice and originality must be preserved

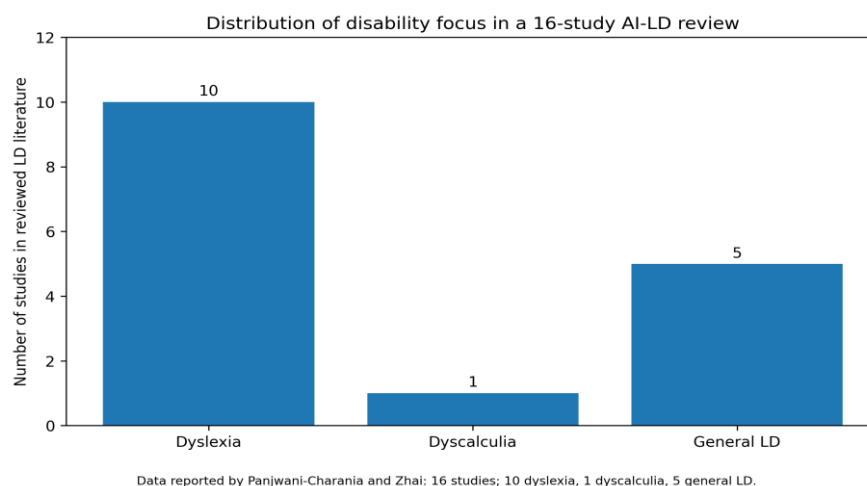


Figure 2. Distribution of disability focus in a reviewed AI-learning-disability evidence base. The figure uses reported counts from Panjwani-Charania and Zhai, not pooled effectiveness data.

4.3 Intelligent Tutoring Systems

Intelligent tutoring systems provide individualized instruction, hints, practice, feedback, and mastery tracking. In special education, they may be useful because they can offer immediate feedback, allow repeated practice without embarrassment, reduce waiting time for teacher assistance, and record fine-grained progress data. However, most intelligent tutoring systems were originally designed for general education populations. A system that adapts only to item accuracy may fail to recognize that a learner's errors arise from language comprehension, visual tracking, working memory, fatigue, anxiety, or motor response constraints. (Anderson et al., 1995; Koedinger et al., 1997; Kulik & Fletcher, 2016; Ma et al., 2014; Létourneau et al., 2025; Zerkouk et al., 2025)

Inclusive intelligent tutoring therefore requires accessibility-by-design, disability-specific validation, transparent adaptation rules, and teacher override. The system should help teachers identify patterns; it should not become a substitute for professional assessment. In practice, intelligent tutoring systems are strongest when they are aligned with curriculum goals, integrated into teacher planning, and used as one component of a broader instructional support system.

4.4 Generative AI and Personalized Content

Generative AI has created new possibilities for special education because it can rapidly transform content into alternative reading levels,

generate examples, create quizzes, summarize complex passages, draft social stories, produce visual schedules, translate text, and support teacher planning. However, generative AI is not automatically pedagogically sound. It can hallucinate facts, oversimplify content, reproduce bias, generate culturally inappropriate examples, or create materials that appear accessible while being conceptually inaccurate. (Holmes et al., 2019; Luckin et al., 2016; UNESCO, 2023b; Hwang et al., 2020; Williamson & Eynon, 2020)

In special education, generative AI should be used primarily as a draft-support tool. Teachers should verify factual accuracy, reading level, alignment with learner goals, cultural appropriateness, and accessibility. UNESCO's guidance on generative AI emphasizes validation, privacy protection, age appropriateness, human-centred use, and policy development. These concerns are intensified when AI is used with children and learners with disabilities.

5. Personalized Support Across Disability Categories

AI in special education should not be discussed as though all disabilities require the same intervention. Different disability categories involve different barriers, supports, and risks. A disability-responsive review must therefore examine AI through learner profiles rather than through tools alone. The same AI function can be beneficial for one learner and harmful for another if context is ignored.

Table 3. Disability-specific AI opportunities and safeguards.

Learner group	AI opportunities	Required safeguards
Dyslexia	Text-to-speech, adaptive reading, spelling feedback, simplified text, multimodal comprehension support	Avoid lowering cognitive expectations; support comprehension and vocabulary, not only decoding
Dyscalculia	Adaptive number sense tasks, visual mathematics support, error diagnosis, stepwise arithmetic feedback	Need stronger empirical evidence, disability-specific validation, and transfer measures
Autism spectrum disorder	Visual schedules, social narratives, structured routines,	Avoid intrusive surveillance, simplistic emotion classification,

Learner group	AI opportunities	Required safeguards
	conversational agents, sensory preference supports	and forced normalization
ADHD	Task chunking, attention prompts, adaptive pacing, executive-function reminders, progress dashboards	Avoid constant monitoring that increases anxiety, stigma, or dependence
Intellectual disability	Simplified instructions, repeated practice, pictorial support, functional learning sequences	Maintain dignity; avoid infantilizing content or low expectations
Hearing impairment	Captioning, speech-to-text, visual alerts, sign-language research, transcript review	Accuracy must be tested across languages, noise levels, and classroom contexts
Visual impairment	Screen readers, OCR, image description, audio navigation, tactile/alternative text support	AI-generated descriptions must be verified for accuracy and instructional relevance
Speech and language impairment	AAC prediction, speech recognition, language practice, alternative expression support	Systems must handle atypical speech and protect voice data
Motor disability	Alternative input prediction, eye-gaze systems, switch access, dictation, interface adaptation	Do not interpret slow response as low understanding
Multiple disabilities	Multimodal access, caregiver-teacher dashboards, individualized prompts, integrated assistive supports	Requires high customization and multidisciplinary oversight

5.1 Learners with Autism Spectrum Disorder

AI applications for autism often focus on social communication, emotion recognition, visual routines, conversational agents, and robots. Structured digital interaction may be useful for some learners because it can be predictable, repeatable, and less socially threatening than spontaneous human interaction. However, autism support must avoid reducing social participation to mechanical recognition of facial expressions. Emotion-recognition AI is especially risky because emotional expression differs across individuals, cultures, neurotypes, and contexts. For autistic learners, ethical design should prioritize communication, self-advocacy, sensory comfort, predictable routines, and meaningful participation rather than forced normalization. (Grynszpan et al., 2014; Khowaja & Salim, 2013; Odom et al., 2015; Parsons & Cobb, 2011; Pennington, 2010; Wainer &

Ingersoll, 2011; Kagohara et al., 2013; Yang & Zhang, 2019)

5.2 Learners with Speech, Language, and Communication Needs

AI-supported speech-to-text, text prediction, and augmentative and alternative communication systems can reduce communication barriers. Prediction tools can reduce the physical and cognitive effort required to produce messages. However, such systems must not speak over the learner or restrict expression to algorithmically predicted phrases. Communication support must preserve agency, choice, and authentic voice. Voice and language data are also sensitive and require strong privacy safeguards. (Beukelman & Light, 2020; Light & McNaughton, 2012; McNaughton & Light, 2013; Hersh & Johnson, 2008; Adebisi et al., 2015)

5.3 Learners with Sensory Disabilities

For learners with visual impairment, AI can assist through optical character recognition, image description, screen-reader enhancement, object recognition, and navigation support. For learners with hearing impairment, AI can support captioning, transcription, visual alerts, and sign-language related research. CAST's Universal Design for Learning guidelines emphasize designing learning environments that reduce barriers and enable meaningful, challenging participation for all learners. AI accessibility tools should be judged by this standard: they must improve access to meaningful learning, not merely provide a technical feature. (Hersh & Johnson, 2008; CAST, 2018; Rose & Meyer, 2002; UNESCO, 2023a; Alnahdi, 2014)

Reliability is a central issue. An incorrect image description, mistranscribed classroom discussion, or inaccurate caption can distort learning. AI accessibility tools therefore require human verification, especially in high-stakes learning, assessment, and safety-related contexts.

5.4 Learners with Physical and Motor Disabilities

AI can support learners with motor impairments through speech input, eye-gaze systems, switch access, predictive typing, gesture recognition, and personalized interface adaptation. The

critical safeguard is that systems must not equate slow response, atypical movement, or alternative input methods with low comprehension. Assessment systems must separate response production difficulty from knowledge level.

6. AI and Teacher Support in Special Education

AI is often discussed from the student side, but special educators also face significant workload demands: individualized education plans, documentation, progress monitoring, differentiated materials, parent communication, behavior data, accessibility conversion, and multidisciplinary coordination. AI may support teachers by generating accessible worksheets, summarizing progress data, suggesting differentiated activities, flagging possible learning barriers, and creating alternative formats. (Okolo & Diedrich, 2014; Baker & Smith, 2019; Linsenmayer, 2025; OECD, 2024; Zawacki-Richter et al., 2019)

However, teacher-facing AI must be designed as decision support, not decision replacement. OECD's work on AI for students with special education needs emphasizes both empowerment and limitations. In special education, teacher-led AI is ethically preferable when educators remain in control and interpret AI outputs alongside observation, assessment, family input, learner preference, and professional judgment.

Table 4. Teacher-facing AI functions in special education.

Teacher task	AI support	Risk if poorly governed	Quality condition
Differentiated content	Generate alternative reading levels, examples, formats, and practice items	May simplify content inaccurately or reduce cognitive demand	Teacher checks accuracy, level, and goal alignment
Progress monitoring	Track skill growth, errors, and practice patterns	May overemphasize measurable behaviors	Combine data with observation and learner context
IEP support	Organize goals, progress evidence, and accommodations	Could produce generic or noncompliant goals	Human team writes and approves all goals
Family communication	Draft updates, summaries, and	Privacy and tone	Remove sensitive details and maintain

Teacher task	AI support	Risk if poorly governed	Quality condition
	accessible explanations	concerns	professional voice
Assessment feedback	Provide formative comments and next-step suggestions	False confidence in automated scoring	Use only for low-stakes formative support unless validated
Behavior support	Detect patterns in incidents or triggers	Risk of biased or decontextualized interpretation	Use functional assessment and human judgment
Accessibility conversion	Create captions, alt text, audio, large print, simplified versions	Errors may reduce access or distort content	Verify all outputs before use

7. Evidence Landscape: Strengths, Weaknesses, and Research Gaps

The evidence base for AI in special education is promising but fragmented. Current work supports the plausibility of adaptive learning, intelligent tutoring, text-to-speech, speech-to-text, and selected assistive technologies. Yet the field remains limited by small samples, short intervention periods, narrow disability focus, weak reporting of implementation context, insufficient attention to teacher training, and limited long-term follow-up. (Rice & Dunn, 2023; Paglialunga et al., 2025; Panjwani-Charania & Zhai, 2023; Létourneau et al., 2025; Zerkouk et al., 2025)

A major issue is the difference between performance improvement inside an AI tool and educational inclusion in real classrooms. A learner may perform better on an adaptive platform but still experience inaccessible assessment, social isolation, low teacher expectations, or limited peer participation. Therefore, future studies should measure participation, self-determination, communication, confidence, independence, and quality of inclusion in addition to test scores. (Shute, 2008; Prinsloo & Slade, 2017; Slade & Prinsloo, 2013; Ifenthaler & Schumacher, 2016; Pardo & Siemens, 2014)

Table 5. Major research gaps in AI for special education.

Research area	Current limitation	Future requirement
Disability coverage	Dyslexia and selected learning disability tools dominate; less work on dyscalculia, intellectual disability, multiple disabilities, and complex communication needs	Broader disability-inclusive research designs and subgroup analyses
Age range	Many tools are not tested across developmental stages	Age-appropriate validation and developmental sensitivity
Outcome measures	Short-term performance often measured more than participation, independence, or self-determination	Longitudinal academic, functional, social, and inclusion outcomes

Research area	Current limitation	Future requirement
Context	Many studies are from higher-resource settings	Low- and middle-income country research and infrastructure-sensitive designs
Ethics	Privacy and bias often discussed conceptually but rarely operationalized	Transparent audit frameworks, consent models, and bias testing
Teacher role	Teachers are often users, not co-designers	Participatory design with special educators and therapists
Accessibility	AI tools may not meet universal design standards	Accessibility-by-design testing with target learners
Equity	Cost, connectivity, and language may restrict access	Affordable, multilingual, offline or low-bandwidth options
Family role	Limited parent/caregiver involvement in tool selection and evaluation	Home-school governance models and transparent communication
Implementation	Pilot studies often lack sustainability evidence	Implementation science, teacher training, and school-level adoption studies

8. Ethical Challenges in AI-Based Special Education

Ethics is not an additional section in AI-special education; it is central to the validity of the field. Learners with disabilities are more vulnerable to misclassification, surveillance, exclusion, and data misuse because their educational profiles often include sensitive information. AI tools may collect academic performance, disability status, behavior data, speech patterns, facial expressions, motor movements, eye gaze, emotional indicators, and family or therapy information. These data are not ordinary educational records; they can shape how a child is labelled, taught, assessed, and understood. (Benjamin, 2019; Eubanks, 2018; Noble, 2018; Binns, 2018; Jobin et al., 2019; Floridi & Cowls, 2019; Mittelstadt et al., 2016)

AI-enabled assistive technology must be evaluated within this wider equity context. A tool that works only in wealthy schools, only in English, or only with high-speed connectivity may widen inequality rather than improve inclusion.

8.1 Data Privacy and Sensitive Learner Profiles

Privacy risks include overcollection, secondary use by vendors, reidentification of supposedly anonymous data, weak consent, long-term retention, and security breaches. Special education data can be especially sensitive because it may reveal disability status, therapeutic needs, behavioral records, medical-adjacent information, or family circumstances. A strong governance model should follow data minimization, purpose limitation, informed consent, encryption, role-based access, deletion rights, and transparent data-sharing agreements. (Ifenthaler & Schumacher, 2016; Pardo & Siemens, 2014; Slade & Prinsloo, 2013; Prinsloo & Slade, 2017; European Commission, 2022; UNICEF, 2021)

8.2 Algorithmic Bias

Algorithmic bias occurs when AI systems produce unequal or inaccurate results for particular groups. In special education, bias may appear when training data underrepresent

disabilities, atypical speech, neurodivergent behaviors, regional accents, minority languages, low-income learners, or culturally diverse communication patterns. A speech-recognition tool may perform poorly for a learner with dysarthria; an attention-detection system may misread autistic gaze patterns; an automated writing evaluator may penalize dysgraphic learners; a behavior prediction system may over-flag students from marginalized communities. These risks make disability-specific bias auditing essential before deployment. (Binns, 2018; Benjamin, 2019; Eubanks, 2018; Noble, 2018; OECD, 2024)

8.3 Transparency, Explainability, and Contestability

Special education decisions must be explainable. A teacher, parent, therapist, administrator, or learner should be able to understand why a system recommends a lower reading level, flags a learner as at risk, changes a task sequence, or suggests a specific intervention. Black-box recommendations are problematic when they influence instructional access, assessment,

placement, or support intensity. Explainability should be paired with contestability: educators and families must have a meaningful route to question, override, or discontinue AI outputs. (Floridi & Cowls, 2019; Jobin et al., 2019; Mittelstadt et al., 2016)

8.4 Autonomy, Dignity, and Overreliance

AI should increase learner agency, not reduce it. Learners with disabilities should not be forced into a narrow pathway because an algorithm predicts limited ability. Systems should allow learners to choose formats, adjust sensory load, express preferences, reject suggestions, and participate in goal-setting. Overreliance is also a risk. Teachers may begin to trust AI recommendations more than professional observation. This is dangerous because learner performance can vary due to fatigue, medication, sensory overload, trauma, family stress, classroom environment, communication barriers, and peer interaction. AI cannot fully interpret these contextual factors. (UNICEF, 2021; UNESCO, 2021; UNESCO, 2025; CAST, 2018; Rose & Meyer, 2002)

Ethical Risk-to-Governance Matrix for AI in Special Education

 Risk domain	 Typical manifestation	 Learner harm	 Governance response
 Privacy	 excessive data, biometrics	 loss of control over sensitive profile	 data minimization; deletion rights
 Bias	 poor fit for atypical speech/gaze	 misclassification or exclusion	 disability-specific testing
 Opacity	 black-box recommendations	 unjustified support changes	 explainable logs; appeal routes
 Overreliance	 AI treated as authority	 teacher deskilling	 teacher-in-the-loop approval
 Equity	 cost/connectivity barriers	 widened digital divide	 low-resource alternatives

Figure 3. Ethical risk-to-governance matrix for AI in special education.

9. Proposed Framework: Responsible AI Integration in Special Education

This review proposes a seven-dimensional framework for responsible AI in special

education: accessibility-by-design, pedagogical validity, disability-specific personalization, teacher-in-the-loop oversight, data privacy and learner rights, bias auditing and transparency,

and dignity, agency, and inclusion. The framework can be used as a pre-adoption checklist, an implementation guide, and a post-adoption audit structure. (CAST, 2018; European Commission, 2022; UNESCO, 2021; UNESCO, 2023b; OECD, 2024; Linsenmayer, 2025)

The framework is deliberately educational rather than purely technical. A technically sophisticated tool is not appropriate if it does not support individualized goals, meaningful participation, accessibility, and learner dignity. Conversely, a simpler tool may be highly valuable if it reliably reduces barriers and strengthens teacher-supported learning.

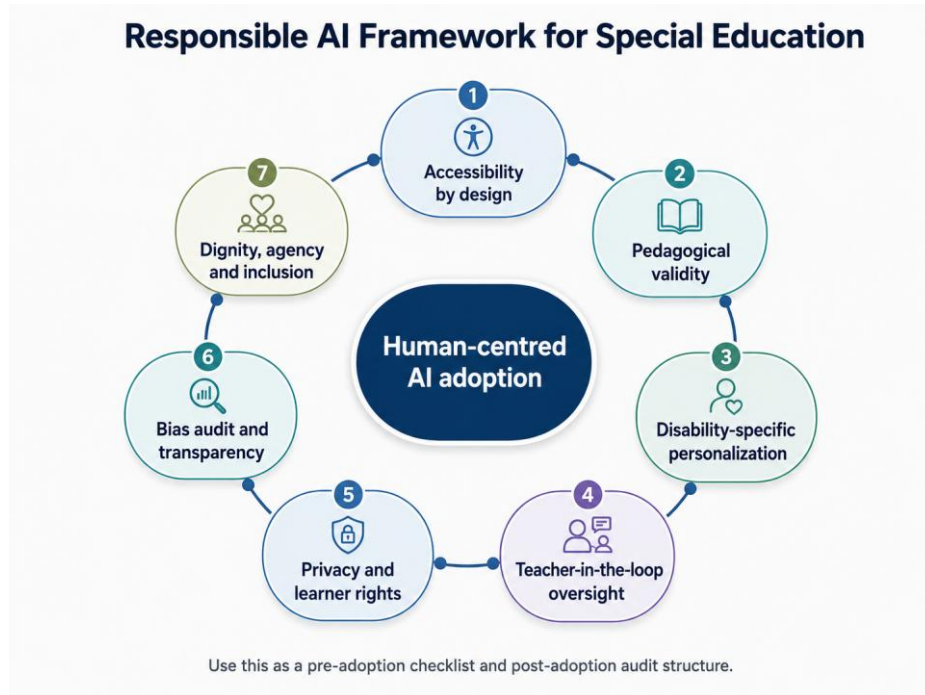


Figure 4. Responsible AI framework for special education.

Table 6. Framework for evaluating AI tools before adoption in special education.

Dimension	Evaluation question	Minimum standard
Accessibility	Can learners with visual, hearing, motor, cognitive, and communication needs use the tool?	WCAG-aligned, multimodal, customizable access
Pedagogical validity	Is the tool based on evidence-informed instruction and aligned with learning goals?	Clear curriculum and IEP relevance
Disability specificity	Has the tool been tested with the target disability group?	Disability-relevant validation and user testing
Teacher oversight	Can teachers review, modify, and override recommendations?	Human control required
Privacy	What data are collected, stored, shared, and deleted?	Data minimization, consent, encryption, and deletion rights
Bias	Has performance been tested across disability, language, gender, and socioeconomic groups?	Independent or documented bias audit

Dimension	Evaluation question	Minimum standard
Explainability	Can recommendations be understood and challenged?	Clear rationale, logs, and contestability routes
Equity	Can low-resource schools use it?	Affordable and infrastructure-sensitive design
Family involvement	Are parents/caregivers informed and included where appropriate?	Transparent communication and consent
Learner agency	Can learners control settings, preferences, and participation?	Choice, autonomy, and dignity preserved

10. Practical Model for Classroom Implementation

AI implementation in special education should follow a phased model rather than a one-time purchase decision. The correct sequence begins with learner need, not with technology. Schools should identify the barrier, map it to an IEP goal

or access requirement, select a tool with evidence and accessibility support, conduct a limited pilot, review data with human expertise, evaluate academic and participation outcomes, and then continue, revise, or discontinue the tool. (Linsenmayer, 2025; Okolo & Diedrich, 2014; Light & McNaughton, 2012; McNaughton & Light, 2013)

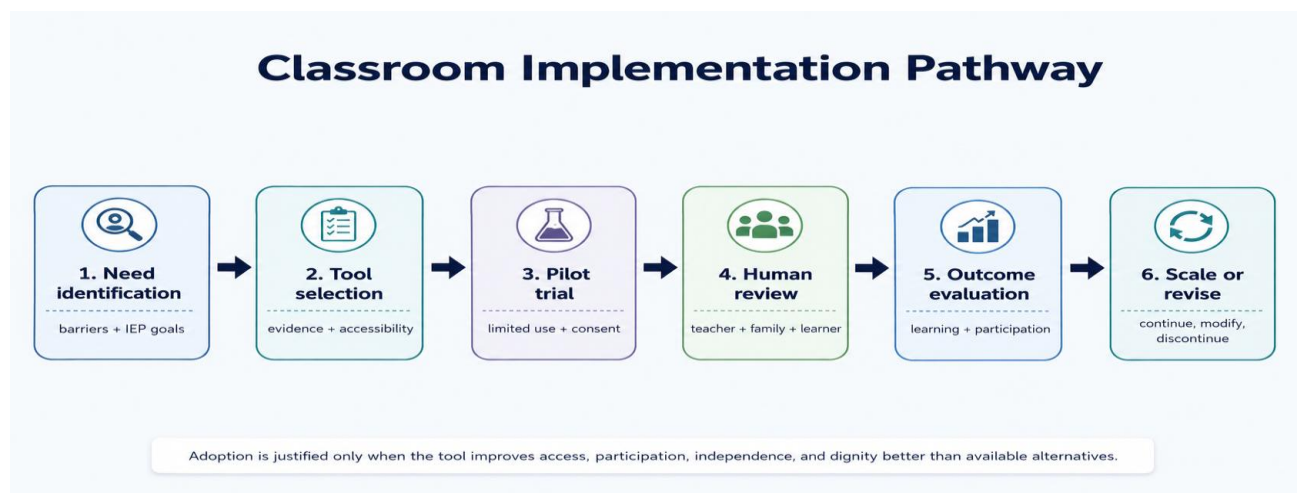


Figure 5. Practical classroom implementation pathway for AI in special education.

Table 7. Phased implementation model for AI-supported special education.

Phase	Action	Responsible persons	Evidence to record
1. Need identification	Identify learner barriers and IEP-linked goals	Special educator, therapist, learner, family	Barrier statement and goal alignment
2. Tool selection	Select AI tool based on evidence, accessibility, cost, language, and privacy	School team and administrator	Tool evaluation checklist
3. Accessibility testing	Test with learner's access mode and assistive technology	Teacher and assistive technology specialist	Accessibility notes and learner feedback
4. Pilot use	Use for a limited period	Teacher and learner	Usage, engagement, and

Phase	Action	Responsible persons	Evidence to record
	with monitoring and consent		difficulty data
5. Outcome evaluation	Measure academic, functional, and participation outcomes	Multidisciplinary team	Progress data, observations, learner voice
6. Revision decision	Continue, modify, scale, or discontinue	IEP/school team	Decision rationale and safeguards

11. Discussion

AI in special education is moving from assistive access toward adaptive decision support. This shift creates both opportunity and risk. The opportunity lies in real-time personalization, multimodal accessibility, formative feedback, teacher support, and learner independence. The risk lies in treating AI outputs as objective truths, ignoring disability diversity, collecting excessive data, and deploying tools before evidence and governance are mature. (Roll & Wylie, 2016; Woolf, 2010; Baker & Inventado, 2014; Siemens & Baker, 2012; Papamitsiou & Economides, 2014; Ferguson, 2012)

A strong special education approach should avoid presenting AI as a miracle solution. AI must be embedded within inclusive pedagogy, Universal Design for Learning, individualized education planning, assistive technology principles, and disability rights. This position aligns with UNESCO's caution that AI and generative AI in education require governance, human-centred design, and pedagogical validation. (UNESCO, 2021; UNESCO, 2023a; UNESCO, 2023b; UNESCO, 2025; UNICEF, 2021)

Three arguments emerge from the review. First, personalization must be disability-responsive. Generic adaptation is not enough; AI must distinguish lack of knowledge from access barriers, sensory barriers, communication barriers, motor barriers, or executive-function barriers. Second, evidence must move beyond short-term performance metrics. Special education outcomes should include communication, independence, participation,

confidence, self-determination, peer interaction, and quality of inclusion. Third, ethical governance must be built before scaling. Privacy, bias, explainability, teacher oversight, and learner agency determine whether AI becomes an inclusion tool or another mechanism of exclusion.

12. Future Research Directions

Future research should prioritize longitudinal classroom trials of AI tools for learners with different disabilities; disability-specific validation of adaptive learning algorithms; comparative studies between AI-assisted instruction and teacher-led evidence-based interventions; AI tools for dyscalculia, intellectual disability, multiple disabilities, and complex communication needs; low-resource and multilingual AI applications; ethical audit models for minors and learners with disabilities; participatory design involving learners, families, special educators, therapists, and disability advocates; and outcome measures that include inclusion, agency, participation, and self-determination rather than only academic accuracy. (Rice & Dunn, 2023; Paglialunga et al., 2025; Panjwani-Charania & Zhai, 2023; Létourneau et al., 2025; Zerkouk et al., 2025)

Another important research direction is the development of implementation science for AI in special education. Schools need practical knowledge about teacher training, infrastructure, costs, data governance, family communication, and sustainability. Evidence from controlled studies is important, but it is not sufficient unless tools can be used responsibly in real classrooms.

13. Conclusion

Artificial intelligence has meaningful potential in special education, particularly through adaptive learning systems, intelligent tutoring, assistive communication, accessibility tools, learning analytics, and teacher decision support. Its greatest value lies in enabling more responsive, multimodal, and individualized learning experiences for learners with disabilities. However, the field remains uneven, with stronger evidence in selected areas such as dyslexia and adaptive reading support and weaker evidence for many disability groups and real-world inclusive classrooms.

AI should not replace special educators, therapists, individualized education planning, or

human relationships. Instead, it should function as a carefully governed support system. Responsible AI in special education must be accessible by design, pedagogically valid, disability-responsive, transparent, privacy-protective, bias-audited, teacher-supervised, and aligned with learner dignity and self-determination. When implemented ethically, AI can support inclusion. When implemented carelessly, it can intensify surveillance, misclassification, inequity, and exclusion. The future of AI in special education therefore depends not only on technical innovation but on disability rights, educational ethics, and human-centred design.

Table 8. Original analytical contribution of this review.

Existing review weakness	How the present paper improves it
Many reviews describe AI tools generally	Links AI tools to disability-specific educational barriers and safeguards
Ethics often discussed separately	Integrates ethics into architecture, adoption, and implementation
Focus often limited to academic performance	Includes participation, agency, dignity, independence, and inclusion
AI described as a technology solution	Positions AI as teacher-supervised and human-centred support
Limited practical guidance	Provides evaluation checklist and phased adoption model
Insufficient attention to low-resource contexts	Connects AI adoption with assistive technology access and equity

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