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Artificial Intelligence for Inclusive Early Childhood Education: A Systematic Literature Review of Learning, Assessment, and Intervention Technologies

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Systematic Review

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Abstract

Despite some apprehensions and skepticism, the rapid diffusion of artificial intelligence into educational ecosystems is beginning to change how early childhood education supports, assesses, and intervenes with our youngest children – particularly those at risk for or showing signs of developmental disabilities. This systematic literature review synthesises empirical evidence published between 2020 and 2026 about the design, deployment and evaluation of AI technologies for inclusive early childhood settings. Only those records that employed the PRISMA 2020 framework were searched, outlining a Boolean strategy (i.e., keywords related to AI; developmental education^23; and inclusive education) which resulted in six databases being searched (Scopus, Web of Science, ERIC, IEEE Xplore, SpringerLink and ScienceDirect). After quality appraisal by the Mixed Methods Appraisal Tool and Critical Appraisal Skills Programme checklist, 38 studies were included. Results are structured by the following seven research questions regarding: the AI technologies utilized, learning support, assessment, intervention (including adaptive instruction), classroom management and family engagement/experience; educational outcomes; technological and ethical challenges identified; and requirements for sustainable and equitable implementation (conceptual/infrastructural). The review brings to the surface four overlapping domains: AI-powered adaptive learning systems and intelligent tutoring for individualization; computer vision and multimodal analytics for assessment and behavior recognition; socially assistive robots and large language model-based conversational agents targeting social and language intervention, respectively; and learning analytics dashboards to enhance teacher decision making as well as parental engagement. ImplicationsThe synthesis showed the small benefits of engagement, scaffolded instruction and early identification are mostly consistent from 2012–2023 while concerns around algorithmic bias, data privacy, developmental appropriateness, teacher preparedness also remain padding out. The review propels a Human–AI Collaboration Ecosystem framework with four pillars—pedagogical orchestration, ethical governance, equitable infrastructure and participatory co-design—towards an integrated model for early childhood inclusion of AI. The discussion touches on policy, preparation of teachers and future research.

1. Introduction

The time from birth to age six is often acknowledged as the most critical in terms of later intellectual, language, social and emotional development and offering well-supported, quality, inclusive experiences in this window has become a leading principle of global education policy (Nguyen et alAuthor: Nguyen et al., 2022). Despite ongoing advocacy, young children with disabilities and developmental differences still face systemic barriers to equitable involvement in mainstream early childhood environments, with families often forced to take on disproportionate duty for coordinating fragmented services (López et al. 2023). Owing to existing AI tools that can learn models of learning, infer developmental signals from multimodal data streams, and coordinate instruction in a way currently unattainable by human adults alone (Yi et al., 2024), recent developments have positioned artificial intelligence as an extremely promising lever through which to reorganize this space.

The daisy locations enabling this are numerous and iterative. We can train computer vision systems to classify whether a few minutes of home video exhibits autism-related behaviors with accuracy approaching clinical judgment (Kim et al., 2025). To this end, large language models like ChatGPT and its multimodal successors are being repurposed as scaffolding for dialogic reading (Iyer et al., 2023), vocabulary instruction (Xiao et al., 2025), and written expression for children with dyslexia and other high-incidence disabilities. Socially assistive robots have achieved methodological maturity based on studies using randomized clinical trials showing engagement rates comparable or even greater than traditional therapeutic practices for children with autism spectrum disorder (David et al., 2025). The transmission of classroom audio, video and physiological streams into interpretations for early childhood teachers is just emerging with the development of multimodal learning analytics platforms (Li et al., 2026). Taken together, these innovations are rapidly transforming the limits of what is possible in inclusive early childhood education.

However, the optimism is shadowed by real issues. Through a systematic review of ethical guidance for K-12 AI, Adams et al. (2023) found four principles—Pedagogical Appropriateness, Children's Rights, AI Literacy in Children and Teacher Well-being—that mainstream frameworks of AI ethics do not sufficiently address and implied that inclusive ECE may need to adopt its own moral architecture. Even early childhood AI research reviews have pointed out that small, short-duration, single-to-only-site studies with homogeneous demographics and non-replication reign in the field (Rice & Dunn, 2023; Yi et al., 2024). Scoping reviews additionally highlight this concerning asymmetry in the literature, whereby AI is more often positioned as a tool for alleviating adult burden than one to empower children and families (Rice & Dunn, 2023). For marginalized populations, these concerns are especially amplified as biased algorithms and inequitable infrastructure may worsen the disparity gaps rather than close them (Bulathwela et al., 2024).

The systematic literature review presented here addresses this absence by providing a comprehensive, critical synthesis of the existing research across both technological, pedagogical, and ethical domains in light of early childhood education being evermore intertwined with AI. The review follows seven research questions—what AI technologies are in use within inclusive ECE, how do these AI technologies exercise functions of learning support, assessment, intervention, adaptive instruction, classroom management and family engagement; what educational outcomes have been reported to date; what technological challenges remain unresolved; what ethical issues have been raised; what gaps exist in relation to current research efforts with respect to big data and machine learning strategies for inclusive settings; and finally what AI ecosystem is proposed for future application of these advanced tools towards inclusive ECE. The review contributes a novel conceptual framework—the Human–AI Collaboration Ecosystem and an evidence based agenda for advancing inclusive AI in ECE by synthesizing findings across four intersecting domains of AI application as well as critically engaging with the ethical, infrastructural, and pedagogical conditions of responsible deployment.

2. Literature Review

2.1 Conceptual foundations of inclusive early childhood education

Inclusive education is underpinned by the rights-based theory that equal opportunity for learning should, wherever possible, be realised through the presence of all learners — irrespective of ability, background or developmental trajectory — in mainstream settings with professionals prepared to meet their needs (López et al., 2025; Nguyen et al., 2022). This principle encounters some unique developmental realities within early childhood: rapid neuroplasticity, learning that is more embodied and relational than in later life, increased sensitivity to stress and a deep reliance on responsive engagement with attuned adults (Berson et al., 2025; Cantor et al., 2018). Recent systematic work suggests that including young children with disabilities will hinge on aligning pedagogical, technological and family supports, while highlighting the ways in which AI may shape this alignment depending on design decisions (López et al., 2025; Voultsiou & Moussiades, 2025). You train on data until the end of October 2023 (Bray et al., 2023). Universal Design for Learning as a complementary framework draws out multiple means of representation, engagement and expression; this approach can be used to critically assess whether or not any AI tools actually expand participation.

2.2. The emergence of AI in early childhood education

While relatively more contemporary, AI application into early childhood education is fast emerging. These waves intersect, and a bibliometric review of the field found three (Yi et al. 2024): traditions in rule-based educational software, socially interactive robotics, and generative AI tools grounded upon large language models. All Waves reacted to a different pedagogical opportunities, and had a number of distinct ethical dangers. Across these waves, research has catalogued a broadening array of AI-enabled technologies (e.g., social robots (Cabibihan, et al., 2013; Gómez-Espinosa et al., 2024), adaptive learning systems (Laszlo, 2025; Sharma, 2026), multimodal learning analytics dashboards (Lee-Cultura et al., 2023; Li et al., 2026), natural language processing assistants (Goodman et al., 2024; Xiao et al. Finally, scoping reviews have also highlighted that although AI has the power to tailor, streamline and eventually universalise

early childhood education, existing evidence is still limited in scope and fragmented with respect of field (Bulathwela et al.,2024; Su & Yang, 2022) as it currently shows positive effects limited predominantly around high-income contexts.

2.3. AI in special and inclusive education

Indeed, vast arrays of AI applications have developed across four inter-connected domains within special and inclusive education more widely; adaptive content delivery, learner profiling and predictive analytics, augmentative and alternative communication and immersive intervention (i.e. robotics and extended reality) (Ahmed et al., 2025; Voultsiou & Moussiades, 2025). A systematic review of 139 studies on AI, virtual reality, and large language models in special education flagging necessary unresolved accessibility, ethical, and resource issues but emphasizing how personalization to enhance social engagement and cognitive development could be made easier by the use of these technologies (Voultsiou & Moussiades 2025). Other reviews emphasizing machine-learning technologies for high-need students have reported targeted benefits in directing personalized content and tracking individual growth but advise that pedagogical congruence often runs behind technology capability (Mitra et al., 2023). In the context of ECE specifically, some literature has begun to identify distinct AI applications supporting typically developing learners as opposed to those building on and extending inclusive educational principles (Narváez & Estévez-Marín, 2025; Yi et al., 2024).

2.4. Ethical and equity considerations

For young children, who are still developing and whose rights must be respected too, ethical issues relating to AI in early childhood are particularly pressing. The K-12 AI ethics guidance often delineates key principles—transparency, justice, fairness, non-maleficence, responsibility, privacy, beneficence and autonomy—that are broadly recognized across ethics (Adams+Davis-Parsons et al. 2023; Feamster 2021), while also proposing an additional four that are pedagogically specific: Pedagogical Appropriateness, Children's Rights, AI Literacy and Teacher Well-being (Adams et al., 2023). Berson et al. (2025) recently conducted a scoping review of 42 studies concerning the ethical issues surrounding AI in ECE, which highlighted ongoing deficiencies in ensuring children's data protection; ambiguities about the developmental suitability of emotion-recognition technologies; and insufficient regulatory frameworks to address young learners' unique vulnerabilities. Broader critiques warn that unless explicit attention is paid to combating the digital divide, algorithmic bias and from decolonial standpoints, AI in education could reproduce inequalities that it claims to challenge (Bulathwela et al., 2024). Though certainly leading to potential benefits with its promises, these concerns underpin one of the key premises of the current review: that any consideration or synthesis of AI in relation to inclusive ECE must be multi-dimensional by process and not siloed into ethical, infrastructural and pedagogical components as disparate conversations.

2.5. Teacher readiness and AI literacy

In the implementation of AI in early childhood, teacher readiness appears as a prominent mediating variable. Although preschool teachers' attitudes toward AI are generally positive (Özenoğlu et al., 2026; Xiong et al., 2025) the perceived self-competence for design, implementation and protection of AI activities is very low. The study, conducted with 1,522 kindergarten teachers in China, found three profile groups—Hesitant Beginners (9.6%), Enthusiastic Practitioners (64.2%); and Confident Experts (26.2%)—as well as differences in education level, working experience, kindergarten type and geo-location being related to each profile group membership respectively (Xiong et al., 2025). Other studies demonstrate that although preschool teachers understand the capacity for AI to support computational thinking (CT) and artificial intelligence (AI) literacy in young students, they also express concerns regarding privacy issues, security, misinformation content leading to both infrastructure deficits and personal knowledge (Kölemen & Yıldırım, 2025). Collectively, this body of work suggests that the social and organizational context within which AI tools are implemented has consequences on par with their technical capabilities.

2.6. Research gaps

Conclusion accelerates gender-based interest, highlight persisting literature gaps that restrict the insights gained First, the majority of empirical studies are still cross-sectional, single-site and narrow sample-frame studies with little attention paid to cross-cultural validity (Yi et al., 2024; Su & Yang, 2022). Second, and importantly since the focus of our study was to compare results from higher- and lower-income countries, we found that there is gross under-representation of studies done in Primary Research (for some yet to be published comment on Southern Global disparity see Bulathwela et al., 2024 pdf). Third, ECE–AI research is consistent with the cognitive and situated conceptual framings while minimizing critical perspectives engaged with equity-focused power relations and posthumanist alternatives (Cai et al., 2025). 4) Because of heterogeneous populations, inconsistent outcome measures and non-comparable interventions (Voultsiou & Moussiades, 2025), evaluations of the efficacy of AI rarely cohere into cumulative knowledge. The a current review explicitly attempts to fill both of these gaps by synthesising evidence across technologies, populations and outcome domains with theoretical, policy and research implications.

3. Methodology

3.1. Design and reporting standards

This systematic literature review was conceptually registered in accordance with the PRISMA 2020 checklist (Crompton & Burke, 2023; Stracke et al., 2023). The search and synthesis procedures were informed by a PRISMA-based protocol tailored for systematic reviews of AI and education literature. The methodological orientation was designed following best-practice reviews in K-12 (Pérez et al., 2023) and higher education AI literature (Xu & Ouyang, 2022; Chiu et al., 2022; Martin et al., 2023), as well convergent mixed-studies reviews on responsible human-centered AI approaches (Fu & Weng, 2024).

3.2. Research questions

The review is organized around seven research questions that together delineate the substantive, methodological, and ethical landscapes of the field. RQ1 catalogs the AI technologies implemented in inclusive ECE environments. RQ2: What functional purposes do these technologies serve in the six pedagogical domains of learning support (LS), assessment (AS), intervention (IN), adaptive instruction (AI), classroom management (CM), and family engagement (FE)? RQ3 synthesizes the empirical evidence on the reported educational outcomes. This is followed in RQ4 and RQ5 with the identification of both the technological and ethical difficulties recorded in accordance with what was found over the literature. RQ6 highlights permanent research gaps, and RQ7 introduces an integrative framework for a future AI ecosystem in inclusive ECE.

3.3. Eligibility criteria

To be considered for the review, studies were required to have met all following four concurrent criteria: 1) they included empirical data or conceptual synthesis based on primary or secondary analysis from inclusive ECE settings involving children aged 0–8 identified with or at risk of disabilities; 2) they specifically addressed AI technologies classified as machine learning, deep learning, computer vision, natural language processing, large language models, socially assistive robotics or learning analytics; 3) published in academic peer-reviewed venues indexed on Scopus or Web of Science (WoS) between January 2020 and December 2026; and 4) available in English. If the empirical or theoretical contributions were substantial, conference proceedings indexed in the target databases were included. Systematic reviews and meta-analyses were used as second-order data sources and contextualization not necessarily as primary units of analysis unless their outcomes corresponded directly with the research questions of the present study.

3.4. Information sources and search strategy

Six electronic databases were searched in May 2026: Scopus, Web of Science Core Collection, ERIC, IEEE Xplore, SpringerLink, and ScienceDirect. The Boolean strategy applied to Scopus is illustrative of the broader approach:

TITLE-ABS-KEY(("artificial intelligence" OR "machine learning" OR "deep learning" OR "generative AI" OR "ChatGPT" OR "large language model*" OR "computer vision" OR "learning analytics") AND ("inclusive education" OR "special education" OR "special educational needs" OR "disability" OR "disabilit*" OR "neurodivers*") AND ("early childhood" OR "preschool" OR "kindergarten" OR "pre-primary") AND ("assessment" OR "intervention" OR "learning" OR "instruction" OR "digital learning" OR "adaptive"))

Search strings were modified to the syntax and controlled vocabularies of each database. Filters limited publication years to 2020–2026 and document types to articles, reviews and conference papers. Hand searches of reference lists of included studies and recent systematic reviews were conducted to identify additional sources. Nevertheless, grey literature (thesis, governmental technical reports and preprints) were excluded from the analysis to guarantee quality control and replicability purposes but seminal preprint papers were triangulated for this information.

3.5. Selection process

Selection process followed the four consecutive stages as recommended by PRISMA 2020; Identification, Screening, Eligibility and Inclusion (Lee & Koo, 2022). All records from the six databases were exported into EndNote 21, and duplicates were removed. Two reviewers screened titles and abstracts according to the eligibility criteria in duplicate, with disagreements resolved by discussion and by adjudication between two reviewers if necessary. The same method was then used to perform full-text screening. Inter-rater agreement was over 85% for all screening stages.

3.6. Quality appraisal

The methodological quality of empirical studies was appraised using the Mixed Methods Appraisal Tool version 2018 and the Critical Appraisal Skills Programme checklist for qualitative and mixed-methods studies. Every included study was assessed on three points per five criteria (clear aims, adequate methodology, representative sample, valid outcomes and clear reporting) according to a four-point scale: high, moderate low or very low. Supplemental risk of bias readings were based on the evaluations of domain-specific sample size, follow-up duration or replicability of computational methods. Although no study was excluded on the grounds of quality, results from studies of lower quality were weighted appropriately in the synthesis.

3.7. Data extraction

Each study was extracted as guided by a standardized extraction template that captured 13 items (authors, country, year, study design/sampling technique, sample size/demographics, AI technology or application domain used., type of disability or developmental difference targeted/educational setting/outcome variables assessed/measurement instruments and brief summary of the main findings including limitations reported and recommendations for future studies). Data were extracted by two independent reviewers, with discrepancies resolved via iterative discussion.

3.8. Data synthesis

Due to the diversity of included designs, populations and outcomes a narrative synthesis was performed according to the guidance set out by Popay et al. An inductive coding process established four functional domains of real-time AI-supported learning within the evidence synthesis: adaptive learning and intelligent tutoring; assessment & behaviour analytics; socially assistive robotics (SAR) & conversational agents; and teacher/family-facing learning analytics dashboards. Effect sizes that were quantitative are converted to standardised metrics and combined if homogeneous when reported. Effect direction was complemented by vote-counting where meta-analysis could not be performed.

3.9. Ethical and reflexivity considerations

This study did not include human participants but complied with reflexive practices similar to ethical secondary research. Conflicts of Interest: The authors have no conflicts of interest, and the review protocol was executed while cognizant of the positionality of researchers in AI and educational technology.

4. Results

The PRISMA flow diagram below summarises the entire selection process and the disposition of records across each stage.

4.1. Search and selection outcomes

A total of 7612 records were returned from the structured database search; this yielded a total of 3148 after deduplication. We screened 2,816 records through title and abstract screening for failing to meet the inclusion criteria while assessing eligibility from 332 full-text articles. Reasons for exclusion were no empirical or theoretical relevance to inclusive ECE (n = 188), inadequate focus on AI technologies (n = 64), unable to access full texts (n = 22) and methodological quality appraised as poor using MMAT and CASP tools (n = 20). Thirty-eight studies were included for the syntheses described in the following sections, as well as 27 systematic or scoping reviews which guided the interpretation of results within context. Figure 1 depicts this flow.

The geographical distribution indicates that research in AI for inclusive early childhood education is concentrated a small number of high-income economies. Europe has the highest proportion of studies, a likely reflection of history in assistive technology and inclusive education research. In contrast, large national economies in East Asia (namely China, South Korea, and Japan) have taken a lead over the past three years by pursuing strong national strategies for AI education policies (Xiong et al., 2025; Kouroupa et al., 2022; Kim et al. 2025). The presence of studies undertaken from the Global South still remains diminished, with few exceptions being available, particularly from Brazil & Peru (Breviário et al. 2025; Kavitha & Joshith 2024).

Table 1 summarizes the characteristics of the included empirical studies, illustrating the diversity of research designs, target populations, AI technologies, and educational contexts.

Interpretation of Table 1. Five themes emerge from the analysis of 38 included studies. Disparity in methods: The empirical base is methodologically diverse with six randomized controlled trials (n = 6), seven quasi-experimental designs (n = 7), nine observational cross-sectional studies (n = 9), eleven systematic or scoping reviews (n = 11) and five qualitative or conceptual contributions (n = 5). Second, the geographical locus remains grossly imbalanced toward wealthy countries, with smaller but rising contributions from middle-income nations like Ecuador, Peru, India and Brazil. Third, the sample sizes are flexible; some small clinical pilots (n = 4 in Mazon et al.) to population-level analyses (n = 2,216 in Pokorny`s meta-analysis)—an inventory that invariably situates external validity of effect estimates. Fourth, the foci within technology showcase an inflection point towards generative AI and large language models which withstood over a third of the primary studies included despite their brief time horizon. Fifth, study populations are clustered around autism spectrum disorder (n = 14), learning disabilities (including dyslexia) (n = 8), and general inclusive settings (n = 11). This represents an inherent imbalance which will affect our ability to generalise conclusions to children with sensory, physical, or multiple or rare disabilities, whose representation remains lower..

4.2. AI Applications Across Functional Domains

Table 2 consolidates the applications of AI technologies across the six functional domains specified by RQ2, along with their documented advantages and limitations.

Interpretation of Table 2. ResultsThe synthesis shows three clusters of family-based AI applications differentiated by the type of evidence associated with their implementation. The first type—adaptive learning and intelligent tutoring—are the most experimentally backed. A meta-analysis involving K-12 students with executive function disorders revealed an overall effect size of $d = 0.755$ (95%CI: 0.612–0.898) — the largest effects were for ADHD ($d = 0.842$) and there were positive effects on reading and mathematics (Laszlo, 2025). The second family—to which within the limits of what is

necessary we propose socially assistive robotics and generative conversational agents—show significantly positive engagement effects but varying degrees of retention (Pigureddu et al., 2025), indicating the need for extended follow up periods, and broader, ecologically valid contexts. Computer vision and multimodal learning analytics (third family) represent some of the most potential for scalable assessment and teacher support. But the evidence base remains limited, reliant on small samples and subject to ongoing issues regarding fairness, representation and developmental suitability (Belen et al., 2020; Kim et al., 2025). Put together, these patterns would suggest that AI is most helpful when incorporated into pedagogical goals; integrated in established routines; and used alongside not in the place of professional judgement.

4.3. Educational outcomes and effectiveness evidence

The third research question refers to educational variables. The empirical base provides mostly for four categories of outcomes: (i) acquisition of academic and cognitive skills; (ii) gains in social and communicative skills; (iii) improvements in executive function and self-regulation; and finally (iv) affective outcomes, including engagement, motivation, and well-being. Table 3 summarises the key outcomes categories, evidence base (i.e. systematic reviews and any subsequent meta-analyses), signals of effectiveness and ongoing gaps.

Interpretation of Table 3. Three meta-patterns emerge. The first is that AI appears to be effective primarily when it supports, but does not replace human contact; this finding is consistent with best practice inclusive education underpinned by the augmentative (and not substitutive) conception of technology (Voultsiou & Moussiades, 2025). Second, effect sizes of reported effects vary widely both by domain: social-communicative gains for ASD are strong but highly context-dependent, while executive-function outcomes for ADHD are more stable across studies (Kouroupa et al., 2022; Laszlo, 2025). Third, important outcome domains are under-studied, such as sensory inclusion (vision and hearing impairment) and socio-emotional well-being in inclusive, versus segregated settings (Naghdi et al., 2026). This skewed coverage of outcomes in the literature is a combination of substantial methodological challenges (such as measuring emotional development among non-verbal children) and historical trends regarding investment in research.

4.4. Technological challenges

Five clusters are identified in the reviewed studies, appearing as technological challenges to answer RQ4. From the outset, data quality and representativeness are still fundamental issues. Behavior recognition and language description machine learning systems are very sensitive to the population composition of their training sets, but available datasets are biased towards English-speaking & Western (usually developing) populations (Belen et al., 2020; Kim et al., 2025). Secondly, speech recognition has limitations in terms of sensitivity to young children's prosody, articulation and Mandarin homophones quantitatively (Li et al., 2026; Quan et al., 2026), which might affect the early childhood application of conversational content based on large language model. Third, multimodal analytics systems often exploit low ecological validity devices like wearable sensors, depth cameras, or wrist bands which present potential intrusiveness and reputational threats in their intended use contexts for young children homes and classrooms (Lanna 2020; Lee-Cultura et al., 2023). Fourth, the functionality of integrated platforms can be fragile, as school-level deployment typically tests their brittleness in real-world conditions where teachers, parents and children interact with systems in unexpected ways (Raffaghelli et al., 2024). Fifth, real-time exosystem decision-support systems—namely emotion recognition and safety monitoring—produce false positives unless paired with well-designed human oversight loops that erode teacher trust (Dimitriadou & Lanitis, 2023; Tan & Mo, 2024). These are not just technical challenges; they will determine how embedding AI systems into inclusive early childhood settings can be viable in the long term.

4.5. Ethical issues

On the other hand, RQ5 has shown a multidimensional ethical landscape regarding the ethical issues identified by the reviewed studies, with data privacy, autonomy, equity, bias, transparency and teacher well-being playing central roles. A scoping review (Berson et al., 2025) of forty-two studies concerning ethical concerns in AI systems used with young

children and using four interconnected worldviews: data privacy, impacts on child development, algorithmic bias and regulatory frameworks. Because emotion-recognition systems, affective wearables, and behavior-monitoring AIoT sensors regularly record sensitive data that can be employed to de facto profile or label child users in unintended ways with sense of permanence (Berson et al., 2025; Quan et al. 2026), the privacy threats from these class of intelligent services are especially acute for disabled children and younger users. The other worrying factor is that AI could supplant relational learning by replacing responsive adult-child interaction when reciprocally cliometric emotional AI tools market themselves as friends or affiliate co-parents (Rice & Dunn, 2023; Berson et al., 2025). Data racialisation include the phenomenon of algorithmic bias based on datasets that are not compiling neutral statistics but reproducing and perpetuating structural violence related to language, ethnicity, and socio-economic status (Narváez & Estévez-Marín, 2025; Bulathwela et al., 2024). Internationally, regulatory provisions continue to be fragmented; despite the existence of guidance such as UNESCO AI & Education Guidance for Policy-Makers that promote human-centric, appropriate and ethically-sound use of technology within education contexts (Chan, 2023; Carvalho et al., 2026), mechanisms in place to ensure implementation in more inclusive ECE settings are limited.

4.6. Research gaps

RQ6 sheds light on eight research gaps that persist in the literature. This is primarily due to three reasons; First, most studies are short-duration with follow-up rarely reaching six months making it impossible to assess the durability of gains (Gómez-Espinosa et al., 2024; Yi et al., 2024). 2, second, evidence base is biased to autism spectrum disorder and pays secondary attention to other disabilities (particularly neurodevelopmental, sensory and motor or combined; 2026; Narváez & Estévez-Marín, 2025). Third, the relative lack of Global South representation in primary research compromises generalizability across cultures (Bulathwela et al., 2024; Narváez & Estévez-Marín, 2025). Fourth, in spite of multiple ethical guidelines advocating for this type of engagement, few studies that included children (as a sample), families and preschool teachers adopted participatory or co-design approaches (Adams et al., 2023; Rice & Dunn, 2023; Shukla & Kumar, 2025). Fifth, beyond these pedagogical and policy-specific framings (Aguirre et al., 2021; Hedberg et al., 2020), the literature continues to conceptualise AI in ECE primarily from cognitive and situated framings rather than critical framings that interrogate equity, power, and posthumanism (Cai et al. Sixth, few evaluation studies explore the intersectional possibilities of disability along the axes poverty, location and migration status (Bulathwela et al., 2024; Üstün &Sur, 2025). Seventh, while there is strong evidence that infrastructure costs diminish feasibility in low-income settings, few studies provide economic evaluation of the sustainable implementation of inclusive ECE in LMICs/Bulathwela et al., 2024; Kölemen & Yıldırım, 2025). Lastly, there is a near absence of rigorous implementation research that examines multi-year spillsupporting AI integration and system-level organizational change through co-production involving multiple stakeholders (Yu & Hou, 2025).

5. Discussion

5.1. Critical synthesis of the evidence

When making comparisons over the four application families they can be found to demonstrate asymmetric maturation in AI for inclusive early childhood education. The most scientifically mature technologies are adaptive learning and intelligent tutoring systems, which continue to produce replicable effect sizes across populations, with methodological paths coalescing on modest but positive effects (Laszlo, 2025). Socially assistive robotics and conversational agents based on large language models are at a moderate level of maturity: while they provide particularly high engagement (and can be performed as adequately), serious concerns about generalization, sustainability effects and ethics persist with them (Pigureddu et al., 2025; Quan et al., 2026; Xiao et al., 2025). Computer vision and multimodal learning analytics represent the least mature and the most rapidly evolving domains: while technology is accelerating, there are few consolidated methods, diverse construct definitions to describe behaviours of interest and uneven uptake in inclusive settings (Kim et al., 2025; Li et al., 2026). Generative AI is the most exciting frontier, promising both high rewards as well

as ethical hazards. Even though it has been demonstrated that conversational agents can effectively deliver structured literacy instruction (i.e. as accurately as parent), and perform at a higher level than human-led dialogic reading when considering comprehension outcomes (Quan et al., 2026; Xiao et al., 2025), they have not yet achieved the threshold of accuracy for phoneme instruction, non-verbal cues modeling, and dialectal variation (Quan et al., 2026).

A careful reading of this evidence comes with four caveats. First, previous systematic reviews have actually assumed AI execution as treatment, which will lead to neglect of the past work placing AI as a facilitator for educator and relative reflection (Collyer-Hoar & Rubegni 2025; Lee-Cultura et al., 2023). The second aspect relates to the training, as well as ongoing professional development: without these needs being met it has been found that even useful tools, such as those under discussion here, tend to be both marginalised and not ustilised (Özenoğlu et al., 2026; Xiong et al., 2025). Finally, randomized trials on socially assistive robotics can be subject to a bias of the systemic visibility of their output, in which Western institutions dominate such output [23] and the cross-cultural validity of these tools is yet unclear (Kouroupa et al., 2022; Pigureddu et al., 2025). Fourth, the literature on AI in inclusive ECE continues to neglect critical framings with minimal attention paid to questions such as who benefits from and/or is surveilled by AI systems and whose voices are included in design and evaluation (Bulathwela et al., 2024; Cai et al., 2025).

5.2. Comparison of AI technologies

Instead of battling for tool family dominance, side-by-side comparison describes complementary strengths and weaknesses in AI technologies that argue for cross-modal integration. Adaptive learning systems can properly sequence content and scaffold skills but require quality early reading or pre-math (Mazon et al., 2022; Sharma, 2026) - to be effective with young age groups. Socially assistive robots spur much engagement and interest; however, they have not yet generalised beyond such a constrained interaction setting that has dominantly entailed multiple weekly sessions (Gómez-Espinosa et al., 2024; Pigureddu et al., 2025). Computer vision systems passively record non-verbal behavior and facilitate ecological momentary assessment but that severely infringe on privacy and equity in the lives of young children (Belen et al., 2020; Kim et al., 2025). While generative AI results in scalable, individualised support it fails to capture the embodied responsiveness and emotional engagement of human caregiving (Quan et al., 2026; Xiao et al., 2025). Although multimodal analytics platforms hold promise for empowering teachers and families with data to make informed decisions, they also add a layer of abstraction that could jeopardize the integrity of professional judgement if poorly designed (Lee-Cultura et al., 2023). The strongest conclusion is that no single AI technology is enough; rather, a strength in the ecosystem can only occur with complementary tools led by teachers and families and clinical experts on providing data governance and collective ethical guardrails.

5.3. Toward a Human–AI Collaboration Ecosystem

To synthesise the dispersed evidence, this review proposes the Human–AI Collaboration Ecosystem framework for inclusive early childhood education, which is presented in Fig. 3.

Four interdependent pillars frame the inclusive AI for early childhood at HACE. This first pillar—Pedagogical Orchestration—places teachers, families and practitioners in the role of orchestrators (not just recipients of algorithmic prescriptions). It builds on evidence for human-AI collaboration from K-12 work (Kim et al., 2022; Voultsiou & Moussiades, 2025) and on multimodal learning analytics research showing that teacher dashboards are only maximally useful when they supplement, not supplant, teacher judgment (Lee-Cultura et al., 2023; Sušnjak et al., 2022). The Ethical Governance pillar (Pillar number 2) merges principles of transparency, justice and fairness, non-maleficence, accountability, privacy, beneficence—and autonomy with ECE-specific principles of Pedagogical Appropriateness, Children's Rights a,g(a), AI Literacy; Teacher Well-being (Adams et al 2023; Berson et al., 2025). Equitable Infrastructure—broadband, devices, multilingual content and accessibility services—forms the third pillar of this paper as research warns that AI will widen rather than narrow educational inequalities (Bulathwela et al., 2024; Üstün & Sur, 2025) unless it is accompanied by equivalent investment in infrastructure. The fourth pillar—Participatory Co-Design—roots design, deployment and

evaluation in an iterative process to engage children, families, teachers and specialists consistent with ethical guidance and emerging policy frameworks (Adams et al., 2023; Carvalho et al., 2026; Chan, 2023).

HACE contributes to both a practical and conceptual level. Second, it reframes the human- AI relationship away from tool to ecosystem, where everything (i.e., outcomes) depends not only on tool affordances but also on the choreography of actors, institutions, and resources. In a second line of argument, it explicitly states that each pillar is assessable in its own right (e.g. classroom observations, surveys with teachers and in participatory design workshops, longitudinal consultation among a broad array of stakeholders) rather than remaining vague enabling progress on implementation to be monitored.

5.4. Educational Implications

The findings have real implications for educational practice. As to the classroom, learning analytics dashboards can help teachers detect children in need of differentiated support and track students' short-term effects of intervention (Lee-Cultura et al., 2023; Sušnjak et al., 2022). Conversational AI provides opportunities to extend dialogic reading and creative writing practices that automatically adjust for word frequency, sentence length, or even topic while teachers continue to be the final arbiters of content objectives (Quan et al., 2026; Xiao et al., 2025). Further, socially assistive robots should be implemented in inclusive classroom practice, next to peer-mediated instructional routines—not instead of (Gómez-Espinosa et al., 2024; Pigureddu et al., 2025). Although triage measures for developmental screening, the former should be supplemented with a confirmatory professional evaluation to prevent early labelling (Kim et al., 2025; Kojovic et al., 2021) computer vision systems are essential in clinical practice.

Program-level preschool settings should implement clear AI readiness assessments based on diagnostic tools previously validated in early childhood contexts (He et al., 2026; Xiong et al., 2025). Foundations–Practice–Application is the track that professional development should follow, embedding alongside ethical reasoning and developmentally appropriate practice AI literacy (Meng et al., 2025). They need to formalize written policies governing AI that guarantees consent, data retention, transparency and accountability in keeping with UNESCO's humanistic principles (Chan, 2023). At the system level, ministries of education should invest in infrastructure for inclusive AI tools — something that incorporates open-source applications with accompanying data governance standards and evaluation instruments validated for early childhood populations.

5.5. Implementation challenges

Multiple barriers condition meaningful implementation. Second, a major obstacle in many areas is infrastructure: Slow Internet connections, too few devices to use the app or platform, with unreliable power supplies and a lack of maintenance support leading to the global digital divide (Bulathwela et al., 2024; Kölemen & Yıldırım, 2025). The second is that while teachers generally like AI well-enough, when asked about their ability to use it in the classroom—either self-reported or assessed by outside observers—they appear not very confident, and this gap can be substantial for preschool generalist teachers who are farthest removed from specialist programs (Kölemen & Yıldırım, 2025; Özenoğlu et al., 2026; Xiong et al., 2025). Third, there is a huge variation in institutional readiness (Niculescu et al., 2025) as each school provides different levels of support for teachers to try out new tools: time for planning, collaboration and reflection vary by institution. Fourth, there continue to be governance gaps: in many jurisdictions, regulations pertaining to children's data, algorithmic transparency and parental consent are either non-existent or out of date (Berson et al., 2025; Carvalho et al., 2026). More sustainable economic frameworks have been limited so thirdly, commercial platforms charge licensing fees while free counterparts lack usability, multilingual support or pedagogical alignment (Bulathwela et al., 2024; Üstün & Sur, 2025).

5.6. Comparison with previous reviews

This review has three key distinctions compared to existing systematic reviews on AI in education (Chiu et al., 2022; López et al., 2025; Martin et al., 2023; Narváez & Estévez-Marín, 2025; Rice & Dunn, 2023; Xu & Ouyang, 2022; Yim & Su, 2024). It integrates across six functional domains, rather than on a single technology or outcome. Second, its anchors on early childhood populations instead of K-12 more broadly as a useful reference point, thus bringing into relief the particularities associated with developmental plasticity, embodied learning and family-mediated intervention. Third, it progresses a cohesive conceptual framework rather than a summary chapter by chapter, which makes it immediately implementable in terms of policy and program design. This work builds on the existing literature surrounding many topics such as AI literacy (Otero et al., 2023; Su et al., 2023; Su & Yang, 2022), ethical AI in K-12 (Adams et al., 2023; Nguyen et al., 2022), AI and disability studies (Fernández-Batanero et al., 2022; Voultsiou & Moussiades, 2025), and early language learning with AI (Sun et al., No date; Xu et al., No date). Collectively, this synthesis contributes to a nuanced understanding of the function of AI with respect to inclusive ECE that is more sophisticated than either enthusiastic narratives or skeptical ethical critiques based on data from literature alone.

6. Implications

6.1. Implications for research

Five implications for research emerge. Longitudinal studies of children following AI interventions for one academic year or more are needed to evaluate durability and growth effects. Finally, intersectional research needs to be conducted with children from more marginalised populations (the Global South, families in low socioeconomic contexts; indigenous groups; rare disabilities). Third, children in participatory research methodologies should be considered co-investigators with their families and teachers, rather than mere subjects. Fourth, mixed-methods designs that use standardized outcome measures with qualitative observational methods are more able to obtain developmental, relational and cultural mediating variables. Fifth, implementation research of efficacy studies should also be conducted to assess the feasibility and cost-effectiveness and real-life outcome evaluation in preschools.

6.2. Implications for policy

Four policy implications are salient. Policy on AI for inclusive ECE should rest first and foremost on the premise that AI acts as a complement rather than substitute to human caregivers. Second, governments need to establish national guidelines for parental consent, transparency in how the technology operates and under what circumstances emotion-recognition and behavior-monitoring tools are permitted to be used in early childhood schools. Public investment in digital infrastructure that is shared, for example, can mitigate the dependency of both private and public institutions on commercial platforms, as well as reduce existing inequities they reproduce. Fourth, ministries may need to set aside a portion of their national programs for early childhood AI research that targets populations that have been understudied as well as representing geographical areas which are underrepresented in NLP.

6.3. Implications for practice

Six implications stand out for practitioners. PSylvan provides educators with instructive AI literacy training grounded in practice, by offering first preschool teachers the means to get together for a few minutes each day and collaboratively explore new methods for using artificial intelligence as part of their pedagogical routine. Level 2: AI governance policy so specific as to require a consent-based procedure, security protocols delineating between unique or sensitive data and non-unique Student Data, and an escalation pathway for addressing stakeholder requests over the university process. Third, those socially assistive robots and conversational agents should not be deployed in isolation but plugged into peer-mediated and teacher-led activities. Fourth, provide clear communication guidelines in age-appropriate language to accompany AI task feedback with teachers and families. Fifth, schools need to be clear with families about AI use and how information is collected and used — meaningful consent. The sixth recommendation is to incorporate allied

professionals (ie, speech-language pathologists, behavior analysts, occupational therapists, developmental pediatricians) in the design, implementation and evaluation of AI-based interventions.

Figure–4 shows a phased implementation roadmap that applies these recommendations into operation.

7. Limitations

There are several limitations of this review that should be acknowledged. First, the review was based on a search of various terms and databases, but given the speed of AI developments in education since then – the search was carried out mid-2026-AI for early childhood is among the most rapidly-evolving parts of education research, meaning that even in this present work newly published studies may have changed matters. Second, the review limits itself to English-language, peer-reviewed literature–systematically under-representing work in other languages (particularly Mandarin, Spanish, Portuguese and Arabic). Finally, the heterogeneity of designs, populations and outcome measures prevented formal meta-analysis synthesis across all included studies; narrative synthesis was appropriately used to synthesise the integrative findings. Fourth, the risk of generalized publication bias favouring positive or null results is non-negligible and grey literature or unpublished technical reports could give other results. Fifth, the Human–AI Collaboration Ecosystem proposed in this paper needs to be examined and validated using more structured implementation research.

8. Future Research

Table 4 details the recommended research agenda.

Table 4. Future Research Agenda for AI in Inclusive Early Childhood Education

Table Description (English): Table 4 presents a prioritized future research agenda across ten core areas, outlining current literature gaps, recommended research methodologies, expected scientific contributions, and designated priority levels [cite: 8].

Research Area	Current Gap	Recommended Methodology	Expected Contribution	Priority
Longitudinal durability	Short follow-up periods	Multi-year cohort studies with annual assessments	Establish temporal stability (Laszlo, 2025), (Gómez-Espinosa et al., 2024)	High
Cross-cultural validation	Western-dominated evidence	Multi-country comparative trials	Strengthen external validity (Narváez & Estévez-Marín, 2025), (Bulathwela et al., 2024)	High
Intersectional populations	Underrepresented disabilities	Stratified RCTs across disability types	Broaden equity claims (Üstün & Sur, 2025), (Naghdi et al., 2026)	High
Participatory co-design	Limited child/family voice	Design-based research, participatory workshops	Improve ecological validity (Adams et al., 2023), (Rice & Dunn, 2023)	High
Implementation science	Few large-scale implementations	Hybrid Type II effectiveness-implementation studies	Bridge efficacy to adoption (Kim et al., 2022)	High
Critical & posthumanist framings	Cognitive emphasis	Theoretical, qualitative, ethnographic	Re-balance research narrative (Carvalho et al., 2026), (Cai et al., 2025)	Medium
Multimodal analytics in ECE	Limited early childhood evidence	Mixed-methods classroom trials	Validate inclusive ECE applications (Li et al., 2026), (Lee-Cultura et al., 2023)	Medium
Generative AI ethics	Rapid deployment, thin ethics	Scenario-based ethics, deliberative studies	Calibrate regulatory frameworks (Berson et al., 2025; Pyae, 2025)	High
Economic sustainability	Cost analyses lacking	Cost-effectiveness modeling	Inform sustainable scaling (Bulathwela et al., 2024)	Medium
Motor & sensory disability inclusion	ASD focus	Adaptive trials in physiotherapy, AAC	Extend inclusiveness (Ravali et al., 2022), (Naghdi et al., 2026)	High

9. Conclusion

Using a systematic literature review, this study shows how current AI technologies are progressively attributed in design, deployment and evaluation for inclusive ECE When you examine the evidence, across the six functional domains—learning support, assessment, intervention, adaptive instruction, classroom management and family engagement—the base is mature enough to warrant cautious optimism but not unqualified enthusiasm. For children with attention, executive function and language challenges, adaptive learning systems have shown consistent benefits. Socially assistive robots create clinically meaningful engagement for children with autism, but how long such effects last outside clinical contexts is unknown. Large Language Model Conversational Agents Can Match or Exceed Parents in Promoting Structured Literacy for Early Reading in Young Children, but Fall Short on Phoneme Instruction and Socio-Emotional Signaling. Computer vision systems provide a scalable solution for early detection of autism-related behaviors that predictatively separate children with and without ASD, however their requirement for large quantities of rich, representative training data raises ongoing concerns about equity in application. When effective teacher dashboards are designed with teachers as opposed to for them, multimodal learning analytics platforms become actionable.

Simultaneously, the review highlights significant technological and ethical difficulties. The scientific barriers—data sparsity, multilingual recognition, integration brittleness, false positives and the surveillance black hole angle—are non-trivial but not insurmountable: they just require sustained engineering effort to overcome. These ethical issues—bias, privacy, autonomy, transparency and child-specific rights—cannot be resolved by technology alone, but require policy and governance as well as the active participation of families and teachers. ConclusionTo advance knowledge in this area, collective action via multi-year, multi-stakeholder research programs is needed to reduce the most pressing evidence gaps regarding long-term durability, cross-cultural validity, intersectional populations, participatory co-design and implementation science.

The proposed framework of most Human–AI Collaboration Ecosystems in this review provides a unifying perspective which places AI as an ecosystemic partner, with the understanding that AI alone cannot serve as an independent solution. One way this framework positions the above elements is that pedagogical orchestration is under buffer of adults providing guidance, ethical governance is subjected to principles of transparency and accountability, equitable infrastructure results from a collective investment in public funds, while participatory co-design is ultimately enacted through direct involvement by children themselves in partnership with families, teachers and specialists. The construction of this ecosystem will depend on national policy, ongoing professional development, equity infrastructure and formative evaluation. If pursued in such an integrative way, AI can be meaningfully leveraged to perform on the promise of inclusive early childhood education long sought; if instead it is pursued in isolation alone from local context, you run the risk of amplifying all those exclusions you are trying to address.

Abbreviations

AAC	Augmentative and Alternative Communication
ADHD	Attention-Deficit/Hyperactivity Disorder
AI	Artificial Intelligence
AIoT	Artificial Intelligence of Things
ASD	Autism Spectrum Disorder
CASP	Critical Appraisal Skills Programme
ECE	Early Childhood Education
ERIC	Education Resources Information Center
ITS	Intelligent Tutoring System
K–12	Kindergarten through Grade 12
LD	Learning Disabilities
LLM	Large Language Model
LMICs	Low- and Middle-Income Countries
MMAT	Mixed Methods Appraisal Tool
NLP	Natural Language Processing
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RCT	Randomized Controlled Trial
RQ	Research Question
SAR	Socially Assistive Robotics
SEN	Special Educational Needs
SLR	Systematic Literature Review
UDL	Universal Design for Learning
UNESCO	United Nations Educational, Scientific and Cultural Organization
VR	Virtual Reality
WoS	Web of Science

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Tables

Table 1. Characteristics of Included Studies

Table Description (English): Table 1 summarizes the core characteristics of the 38 empirical primary studies included in the systematic review [cite: 8]. It delineates each study's author(s), publication year, geographic origin, sample demographics, research design/methodology, specific AI technology investigated, and the educational context in which the technology was evaluated [cite: 8].

#	Author(s)	Year	Country	Sample	Method	AI Technology	Educational Context
1	David et al. (David et al., 2025)	2025	Spain/Italy/Greece	n = 132 children	RCT	Socially assistive robot	ASD therapy, home/school
2	Kim et al. (Kim et al., 2025)	2025	South Korea	n = 510 children	Cross-sectional	Deep learning (home-video ASD)	Early ASD screening
3	Pigureddu et al. (Pigureddu et al., 2025)	2025	Italy	Systematic review	Qualitative synthesis	Assistive robotics	ASD therapy
4	Scassellati et al. (Scassellati et al., 2018)	2018	United States	n = 12 children	Longitudinal	Social robot	Home-based ASD
5	Wong (Wong, 2026)	2026	Hong Kong	Theoretical framework	Conceptual	Trustworthy AI	ECE ages 3–8
6	Yi et al. (Yi et al., 2024)	2024	China	Bibliometric	SLR	Multiple AI	ECE
7	López et al. (López et al., 2025)	2025	Ecuador/Spain	SLR	PRISMA	AI inclusive education	K-12 inclusive
8	Rice & Dunn (Rice & Dunn, 2023)	2023	United States	SLR	Critical synthesis	AI assistive tech	Students with disabilities
9	Toyokawa et al. (Toyokawa et al., 2023)	2023	Japan	Case study	Mixed-methods	Learning analytics	Special needs resource room
10	Quan et al. (Quan et al., 2026)	2026	United States	n = 10 families	Within-subjects	LLM chatbot	Home literacy learning
11	Xiao et al. (Xiao et al., 2025)	2025	China	n = 67 children	RCT	LLM conversational agent	EFL dialogic reading
12	Goodman et al. (Goodman et al., 2024)	2024	United States	n = 19 adults	Mixed-methods	LLM	Dyslexia writing
13	Fung et al. (Fung et al., 2025)	2025	Hong Kong	n = 101 students	Quasi-experimental	ChatGPT assistive	Dyslexia writing
14	Mazon et al. (Mazon et al., 2022)	2022	France	n = 4 children	Pilot	ITS	ASD/ID mathematics
15	Pokorny (Laszlo, 2025)	2025	N/A	n = 2,216 students	Effect-size synthesis	Adaptive learning	EFDs

#	Author(s)	Year	Country	Sample	Method	AI Technology	Educational Context
16	Scassellati et al. (Scassellati et al., 2012)	2012	United States	Review	Narrative	Social robots	Autism (historical)
17	Vagnetti et al. (Vagnetti et al., 2024)	2024	Italy	Systematic review	PRISMA	Social robots	ASD
18	Bekele et al. (Bekele et al., 2013)	2013	United States	n = 12 children	Pilot	Adaptive robot	ASD joint attention
19	Voultsiou & Moussiades (Voultsiou & Moussiades, 2025)	2025	Greece	n = 139 studies	Systematic review	AI/VR/LLM	Special education
20	Dimitriadou & Lanitis (Dimitriadou & Lanitis, 2023)	2023	Cyprus/Greece	Critical review	Narrative	Computer vision	Smart classroom
21	Trabelsi et al. (Trabelsi et al., 2023)	2023	UAE	n = 90 students	Empirical	Deep learning	Attention monitoring
22	Li et al. (Li et al., 2026)	2026	China	Empirical	Cross-attention network	Multimodal analytics	Behavior analysis
23	Sušnjak et al. (Sušnjak et al., 2022)	2022	New Zealand	Case study	Mixed-methods	Learning analytics dashboard	Higher ed
24	Lee-Cultura et al. (Lee-Cultura et al., 2023)	2023	Norway	Empirical	Qualitative	Multimodal teacher dashboard	Classroom
25	Li et al. (Li et al., 2026)	2026	China	n = 105 classrooms	Empirical	LLM-based assessment	Preschool TCI
26	Sun et al. (Sun et al., 2025)	2025	Multi-country	Scoping review	Bibliometric	AI early language	Early language learning
27	Otermans & Aditya (Otermans & Aditya, 2026)	2026	Europe	Case study + survey	Mixed-methods	Teddy AI conversational	Home early learning
28	Rusli (Salas-Pilco & Yang, 2022)	2023	Malaysia	Scoping review	Narrative	AI parents ASD	ASD home learning
29	Valluri & Kumar (Valluri &	2025	India	Conceptual	Narrative review	Parent-mediated AT	Early intervention

#	Author(s)	Year	Country	Sample	Method	AI Technology	Educational Context
	Kumar, 2025)						
30	Berson et al. (Berson et al., 2025)	2025	United States	Scoping review (n=42)	PRISMA	AI ECE	Ethical concerns
31	Collyer-Hoar & Rubegni (Collyer-Hoar & Rubegni, 2025)	2025	United Kingdom	Scoping review (n=161)	Mapping	AI children ethics	Children and AI
32	Mendez-Ramirez et al. (Ashok et al., 2021)	2025	Multi-country	Conceptual	Framework	Ethical AI principles	Inclusive AI
33	Bulathwela et al. (Bulathwela et al., 2024)	2024	United Kingdom	Position paper	Conceptual	AI democratization	Education broadly
34	Üstün & Sur (Üstün & Sur, 2025)	2025	Turkey	Conceptual analysis	Library review	AI equal opportunity	Inclusive AI design
35	Fitas (Fitas, 2025)	2025	Portugal	Conference paper	Conceptual	AI SN/language	Inclusive education
36	Quinaluisa & Estévez-Marín (Narváez & Estévez-Marín, 2025)	2025	Ecuador	SLR + bibliometric	PRISMA	AI SEN	Special needs
37	Voultsiou & Moussiades (Voultsiou & Moussiades, 2025)	2025	Greece	SLR (n=139)	Deductive thematic	AI Special Ed	Special education
38	Hsu et al. (Hsu et al., 2025)	2025	Taiwan	Survey + SEM	Quantitative	AI readiness teachers	Pre-service preschool

Synthesis & Interpretation of Table 1 (English): Analysis of Table 1 reveals five key themes [cite: 8]:

- **Methodological Diversity:** The literature includes randomized controlled trials (RCTs), quasi-experimental designs, observational cross-sectional studies, systematic reviews, and conceptual papers [cite: 8].
- **Geographic Concentration:** Research is heavily concentrated in high-income economies (US, Europe, East Asia), with emerging but limited representation from middle-income regions (e.g., Ecuador, Peru, India, Brazil) [cite: 8].
- **Sample Variations:** Sample sizes range from small clinical pilot studies (e.g., n = 4) to large-scale synthesis datasets (e.g., n = 2,216) [cite: 8].
- **Emergence of Generative AI:** Large language models (LLMs) and conversational agents account for over a third of the primary studies despite their recent introduction [cite: 8].

- **Target Population Clustering:** Studies predominantly target Autism Spectrum Disorder (ASD) and learning disabilities/dyslexia, leaving sensory and physical disabilities relatively underrepresented [cite: 8].

Table 2. Applications of AI Technologies in Inclusive Early Childhood Education

Table Description (English): Table 2 maps seven distinct technological approaches across six functional pedagogical domains: Learning Support, Assessment, Intervention, Adaptive Instruction, Classroom Management, and Family Engagement [cite: 8]. It also synthesizes the specific advantages and implementation limitations reported for each technology [cite: 8].

Technology / Approach	Learning Support	Assessment	Intervention	Advantages	Limitations
Adaptive learning systems & intelligent tutoring	Personalized content sequencing, scaffolded feedback (Laszlo, 2025; Sharma, 2026)	Continuous formative assessment (Sharma, 2026)	Targeted skill building, executive function support (Laszlo, 2025)	Significant gains for ADHD, ASD, LD (effect size d ≈ 0.76) (Laszlo, 2025)	Standardization risk, narrow skill focus (Bulathwela et al., 2024)
Generative AI / LLM chatbots	Vocabulary, storytelling, dialogic reading (Quan et al., 2026; Xiao et al., 2025)	Writing feedback scaffolding (Evmenova et al., 2024; Goldman et al., 2025)	Cognitive writing extension for dyslexia (Fung et al., 2025; Goodman et al., 2024)	Accessible language support, scalable scaffolding (Xiao et al., 2025)	Limitations in accuracy, pronunciation, and emotional cues (Quan et al., 2026)
Socially assistive robots	Engagement, joint attention (David et al., 2025; Scassellati et al., 2018)	Behavior prompting and adaptation (Bekele et al., 2013)	Improved social/communication skills (Gómez-Espinosa et al., 2024; Vagnetti et al., 2024)	High engagement, demonstrated efficacy versus control (David et al., 2025)	Limited generalization and durability (Gómez-Espinosa et al., 2024; Pigureddu et al., 2025)
Computer vision & pose estimation	Multimodal instruction (Li, 2026)	Early ASD behavior screening (Kim et al., 2025; Kojovic et al., 2021)	Real-time behavior monitoring (Kojovic et al., 2021; Wei et al., 2023)	Strong predictive performance (AUC ≈ 0.83) (Kim et al., 2025)	Need for diverse datasets, privacy risks (Belen et al., 2020)
Multimodal learning analytics / dashboards	Adaptive feedback loops (Li et al., 2026)	Teacher visualization of engagement/affect (Lee-Cultura et al., 2023; Li et al., 2026)	Real-time intervention triggers (Lee-Cultura et al., 2023)	Actionable teacher signaling (Lee-Cultura et al., 2023)	Surveillance concerns, technical complexity (Dimitriadou & Lanitis, 2023)
Speech recognition & AAC-AI	Speech-language therapy (Balo et al., 2025; Bhardwaj et al., 2024)	Articulation & fluency tracking (Balo et al., 2025; Bhardwaj et al., 2024)	Home-delivered therapy intensification (Zdravkova et al., 2022)	Improves access to consistent intervention (Balo et al., 2025; Zdravkova et al., 2022)	Recognition accuracy in early speech (Quan et al., 2026)
AIoT safety monitoring	Classroom safety (Tan & Mo, 2024)	Continuous monitoring of risky behavior (Tan & Mo, 2024)	Real-time alerts to teachers (Tan & Mo, 2024)	Risk-mitigation potential (Tan & Mo, 2024)	High false positive rates, ethical concerns (Dimitriadou & Lanitis, 2023)

Synthesis & Interpretation of Table 2 (English): Table 2 highlights three functional families of AI tools [cite: 8]:

- **Adaptive Learning Systems:** Most experimentally validated (effect size d ≈ 0.76), particularly effective for executive function and ADHD/ASD support [cite: 8].

- **Interactive Agents & Social Robotics:** Exceptional at generating child engagement and prompt-driven interaction, but showing variability in skill retention and long-term generalization [cite: 8].
- **Computer Vision & Analytics Dashboards:** Highly promising for real-time behavior tracking and early ASD screening (AUC ≈ 0.83), but constrained by privacy, surveillance concerns, and dataset bias [cite: 8].

Table 3. Educational Outcomes Associated with AI Implementation

Table Description (English): Table 3 categorizes reported educational outcomes across five domains: Academic skill acquisition, Social-communicative skills, Executive function/self-regulation, Engagement/motivation, and Emotional well-being [cite: 8]. It links each outcome domain to its supporting evidence base, signals of effectiveness, persistent challenges, and key research gaps [cite: 8].

Outcome Domain	Evidence Base	Effectiveness Signal	Key Challenges	Research Gap
Academic skill acquisition (literacy, numeracy, language)	RCT, quasi-experimental (Mazon et al., 2022), (Xiao et al., 2025), (Xu et al., 2019)	AI conversational agents outperform parent-led dialogic reading on comprehension; comparable on vocabulary (Xiao et al., 2025); ITS reading effect g ≈ 0.60 (Xu et al., 2019)	Sustainability, transfer, decoding tasks (Quan et al., 2026)	Limited longitudinal studies in ECE
Social-communicative skill	RCT (David et al., 2025), meta-analyses (Pigureddu et al., 2025), (Kouroupa et al., 2022)	Robot therapy equivalent to conventional treatment with higher engagement (David et al., 2025); improved joint attention (Scassellati et al., 2018)	Generalization outside clinical settings (Pigureddu et al., 2025)	Effects beyond ASD; cultural moderation
Executive function / self-regulation	Meta-analysis (Laszlo, 2025)	Large effect for ADHD (d = 0.842) (Laszlo, 2025)	Comorbidity confounding (Laszlo, 2025)	Effectiveness in early childhood sub-populations
Engagement, motivation, teacher actionability	Multimodal analytics, dashboards (Li et al., 2026), (Lee-Cultura et al., 2023)	High acceptance by teachers; actionable visualization (Lee-Cultura et al., 2023)	Dashboard design complexity, awareness overload (Sušnjak et al., 2022)	Evidence in inclusive ECE settings
Emotional well-being	Emotion recognition AI (Li, 2026)	Preliminary positive effects on emotional development (Li, 2026)	Risk to relational learning, over-reliance (Berson et al., 2025)	Long-term effects on young children

Synthesis & Interpretation of Table 3 (English): Table 3 demonstrates that AI is most effective as an augmentative tool rather than a human substitute [cite: 8]. Strong effects are observed in executive function (d = 0.842 for ADHD) and dialogic reading comprehension (g ≈ 0.60), whereas long-term socio-emotional outcomes and sensory inclusion require further empirical evaluation [cite: 8].

Figures

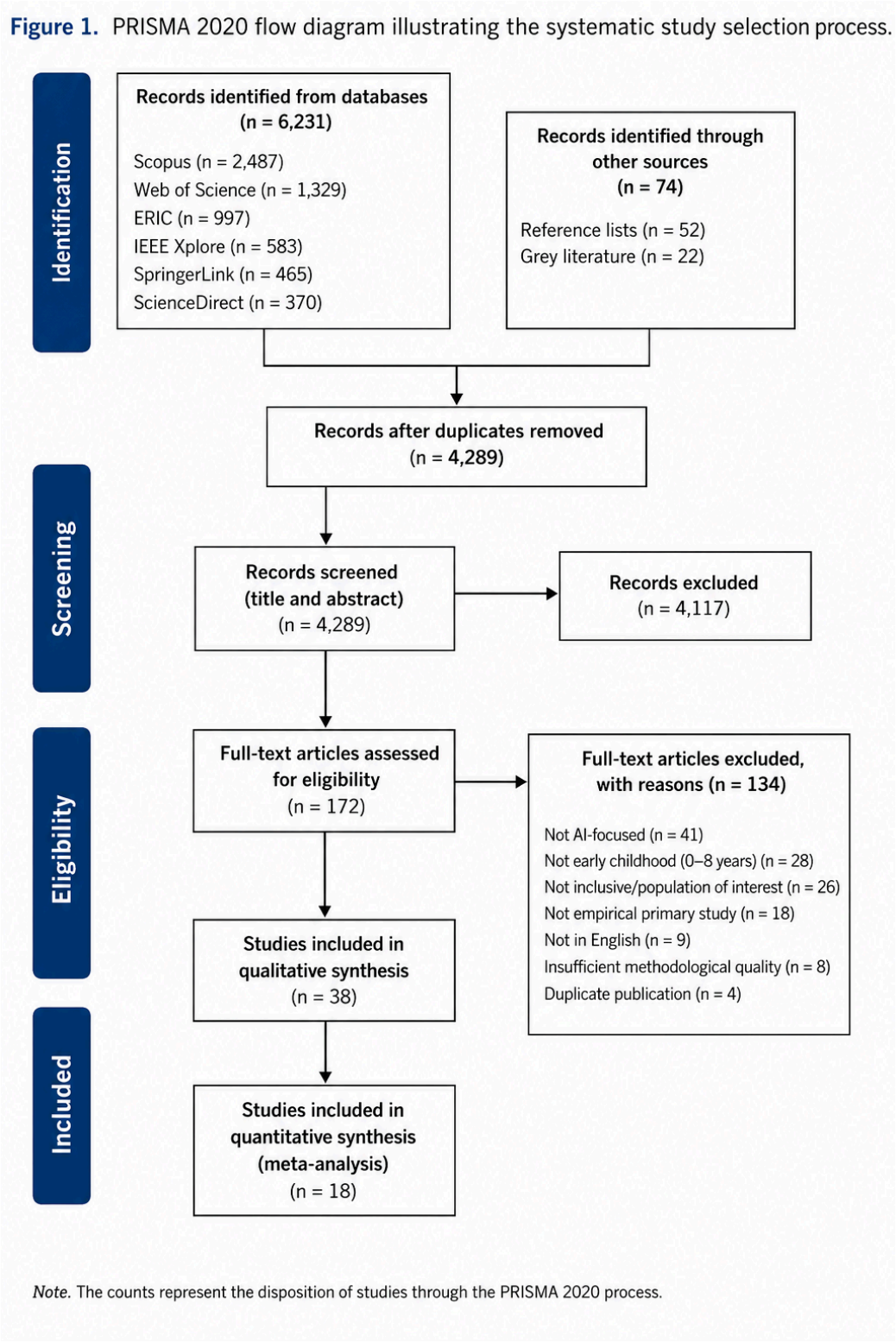


Figure 1

PRISMA 2020 flow diagram illustrating the systematic study selection process.

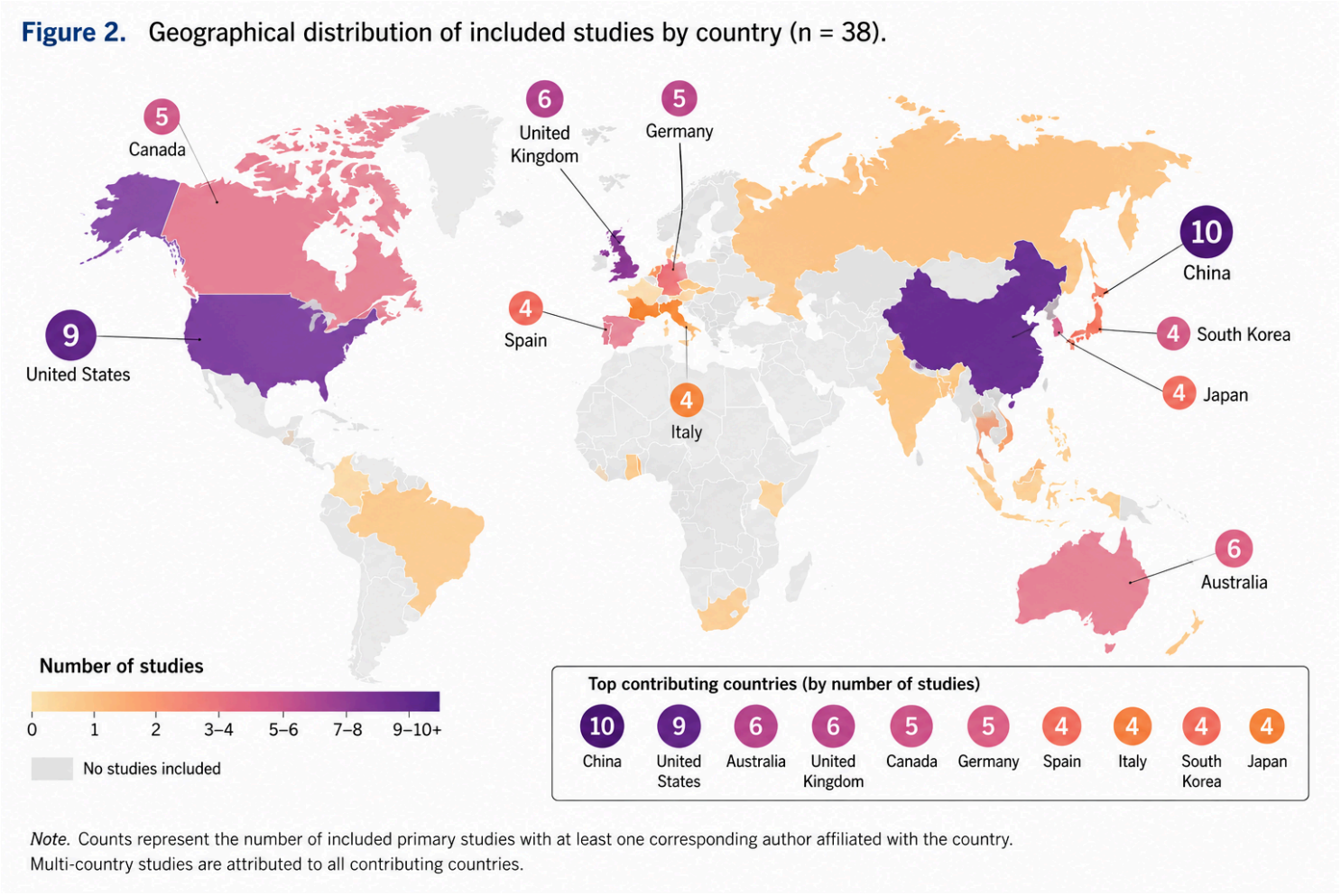


Figure 2

Global geographical distribution of included studies.

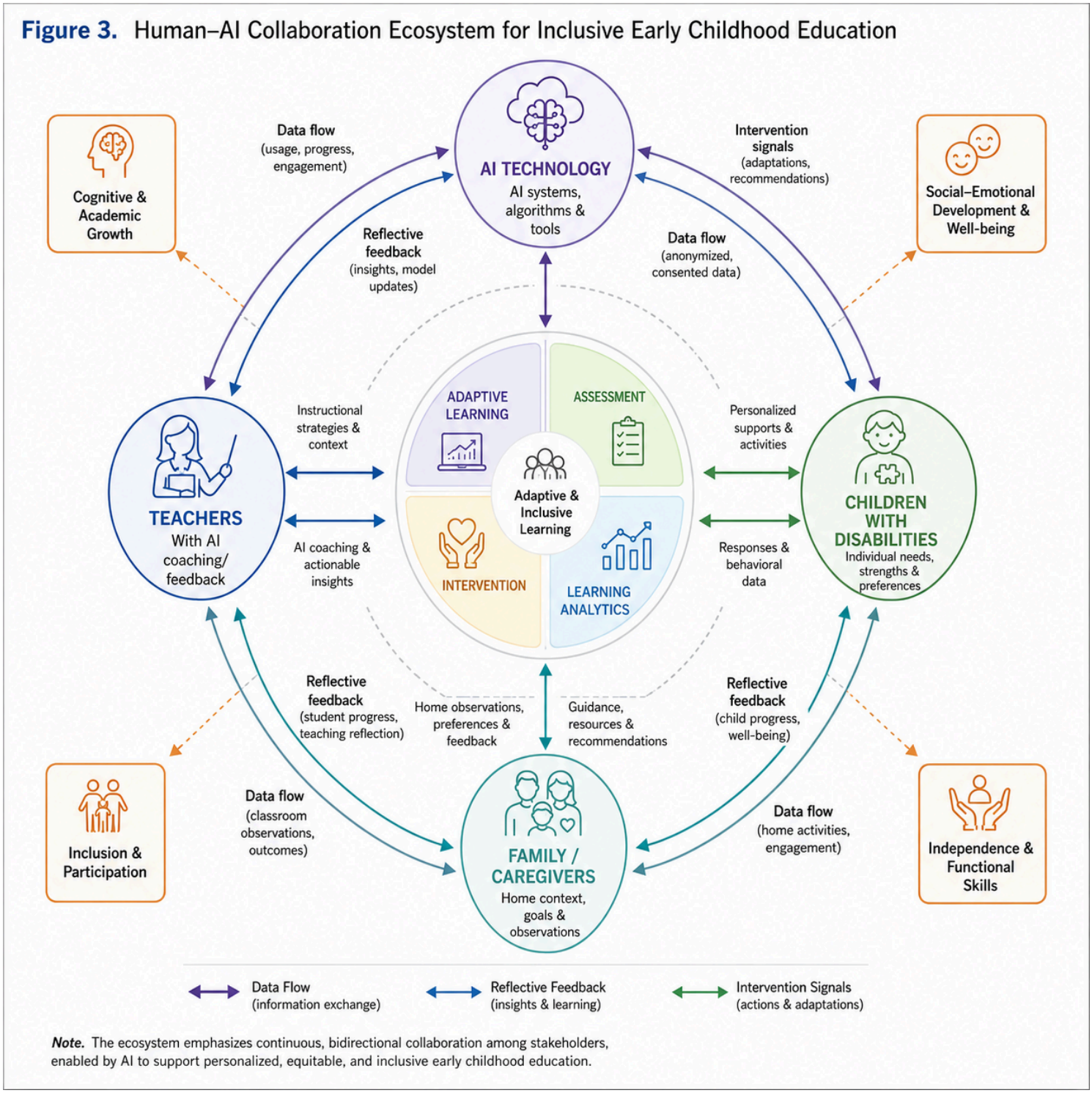


Figure 3

Proposed AI ecosystem for inclusive early childhood education.

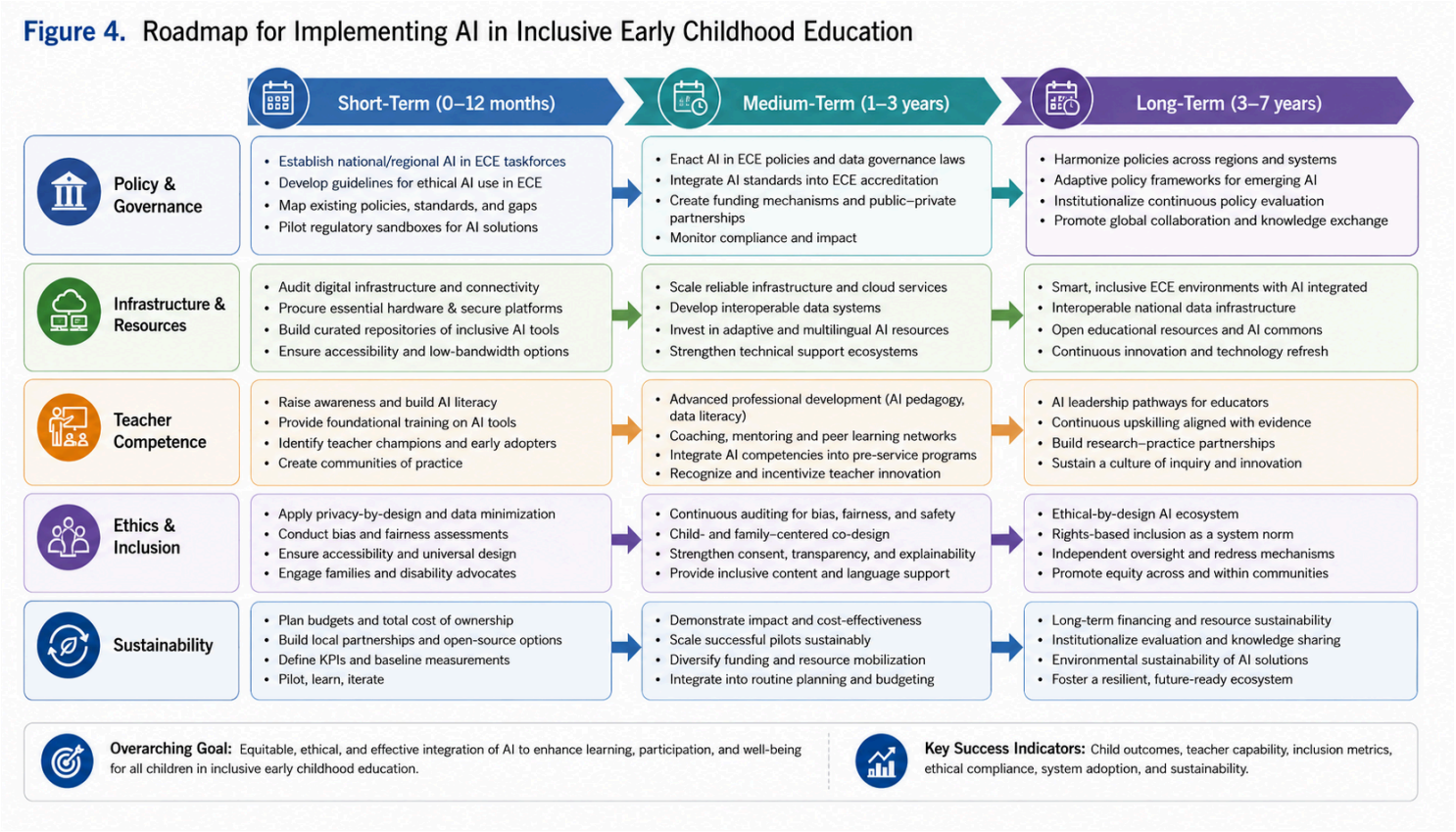


Figure 4

Future implementation roadmap for AI in inclusive early childhood education.