

Neuroeducation and the influence of AI on early childhood education: A systematic review



Betty Burbano-Enríquez^a  | Hugo Moncayo-Cueva^a | Andrea Andrade-Zuleta^b

^aFaculty of Education, Universidad Tecnológica Indoamérica, Quito, Ecuador.

^bFaculty of Education, Universidad de Otavalo, Imbabura, Ecuador.

Abstract Neuroeducation integrates knowledge from neuroscience, psychology, and pedagogy to inform evidence-based teaching strategies, especially during early childhood—a stage of heightened brain plasticity and foundational learning. Concurrently, artificial intelligence (AI) offers adaptive and personalized tools that can support neurocognitive development through data-driven educational interventions. This systematic review examines the empirical convergence between neuroeducation and AI in early childhood education, analyzing how AI-enabled tools reflect and apply neuroeducational principles. The review followed the PRISMA protocol to ensure methodological rigor. A total of 735 records were initially identified across five major databases (Scopus, Web of Science, PubMed, PsycINFO, and Elsevier). After applying strict inclusion and exclusion criteria, 18 peer-reviewed studies published between 2020 and 2025 were selected for final analysis. Each study was classified according to a four-part taxonomy of AI interaction modalities: embodied robots, screen-based systems, voice-only interfaces, and multimodal environments. The findings reveal that AI-supported interventions can enhance executive functions, cognitive flexibility, attention regulation, and socioemotional development when designed in alignment with neurodevelopmental needs. Embodied and multimodal AI systems demonstrated effectiveness in fostering engagement, interaction, and social cognition, while screen-based and voice-only systems proved useful for cognitive and linguistic skills. Ethical challenges were also identified, including privacy concerns, emotional dependency, equity of access, and developmental appropriateness. This study highlights that the integration of AI and neuroeducation requires careful interdisciplinary collaboration among educators, technologists, and policymakers. Beyond summarizing current evidence, the review underscores the importance of adopting developmentally appropriate practices, ensuring ethical safeguards, and fostering teacher training in AI-informed pedagogy. By synthesizing empirical research, this work provides a conceptual and practical foundation for advancing early childhood education through a neuroeducational framework enriched by AI technologies.

Keywords: artificial intelligence, brain plasticity, cognition, educational technology, learning development, neurology

1. Introduction

The interplay between neuroscience and education has gained substantial prominence in recent decades, highlighting the vital highlighting the crucial need to examine how the brain encodes, retains, and recalls information, as well as the ways these functions shape learning performance and teaching practices (Prieto-Navarro, 2020). Neuroeducation, an interdisciplinary domain that synthesizes insights from neuroscience, psychology, and cognitive science, seeks to elucidate the biological and cognitive mechanisms underlying learning and development. Its principal objective is to enhance educational practices by translating empirical neuroscientific findings, such as those related to brain plasticity, memory consolidation, attention regulation, motivation, and executive functioning, into effective pedagogical strategies and curriculum designs (Barrera-Rodríguez et al., 2022; Carvalho et al., 2021; De Souza Martins et al., 2019).

Early childhood represents a critical and sensitive developmental period characterized by pronounced neuroplasticity and the presence of sensitive windows during which the brain is especially receptive to environmental stimuli (Lascano-Arias et al., 2025). These early stages are foundational for the establishment of cognitive, emotional, and social capacities that influence lifelong learning trajectories (Burgueño-López, 2022). Neuroeducation emphasizes the importance of creating emotionally supportive and stimulating learning environments that align with the functional architecture of the developing brain. Core principles include fostering positive emotional contexts, optimizing attention through engaging in meaningful activities, and personalizing interventions to meet the unique developmental profiles and needs of individual learners (Moreta-Herrera et al., 2025). These approaches encourage active, project-based, and collaborative learning experiences that foster more meaningful comprehension and long-term consolidation of learning (Figuroa & Farnum, 2020; Jiménez-García et al., 2023). Integral to this approach is the specialized training of educators, which equips them with the necessary knowledge and tools to apply neuroscientific principles effectively in the classroom, thereby optimizing cognitive and socioemotional



development and supporting each child's potential within a scientifically grounded pedagogical framework (Bellettini Vela et al., 2024; González Gutiérrez & González Gutiérrez, 2024).

Parallel to these developments, AI has quickly positioned itself as a major driver of change within education, comprising diverse tools such as adaptive learning platforms, intelligent tutoring systems, educational robotics, and interactive applications that analyze learner data in real time to provide personalized feedback and scaffolded learning experiences (Bonilla-Jurado et al., 2024; Ouyang & Jiao, 2021).

These technologies hold promises for enhancing engagement, accessibility, and inclusivity in education. By continuously monitoring individual learner performance and preferences, AI systems can tailor educational content and pacing, thereby offering dynamic, personalized learning environments. This adaptability aligns closely with neuroeducational principles, as it allows for interventions that capitalize on neuroplasticity and support executive functions such as working memory, inhibitory control, and cognitive flexibility, all of which are crucial for early childhood learning (Harry, 2023; Zhang & Aslan, 2021).

Despite the apparent synergy between neuroeducation and AI, the literature reveals a considerable gap in explicit integration in these fields, especially within the context of early childhood education. Most studies treat neuroeducation and AI as separate or loosely connected domains, often focusing predominantly on technological development or on neuroscientific theory in isolation without robustly linking AI applications to neurodevelopmental frameworks or early childhood pedagogy (Gulz et al., 2020; Zhao, 2021). This disconnect limits the understanding of how AI-enabled educational interventions can be purposefully designed and optimized to support brain-based learning processes, particularly during sensitive developmental periods.

The present systematic review seeks to overcome this limitation by thoroughly analyzing available empirical evidence positioned at the crossroads of neuroeducation, artificial intelligence, and early childhood development, understood as the period from birth to eight years. This review investigates how AI-driven educational interventions incorporate neurocognitive principles to influence cognitive, social, and emotional developmental outcomes. It further explores the differential impact of various AI interaction modalities, including physically embodied robotics, screen-based interfaces, voice assistants, and multimodal systems, on learning processes within neuroeducational frameworks. Moreover, the ethical implications of applying AI in early childhood settings, such as concerns related to privacy, emotional attachment, and equitable access, are examined to offer an integrated perspective on both the challenges and the opportunities associated with this convergence.

By synthesizing evidence across diverse empirical studies, this review aspires to develop a coherent theoretical and practical framework that guides educators, technology developers, and researchers in the effective integration of neuroscience and AI in early childhood education. This interdisciplinary and evidence-based approach has the potential to revolutionize personalized learning by grounding technological innovation in a sophisticated understanding of brain development, cognitive psychology, and educational theory. Ultimately, this integration promises to ensure that educational innovations are both developmentally appropriate and responsive to the complex needs of young learners within an increasingly digital and technology-mediated educational landscape.

The primary research question framing this systematic review is “What is the synergistic role of neuroscience and AI in enhancing early childhood education?” This question defines the scope and methodological direction of the study, guiding a systematic analysis of the current evidence base regarding the integration of neuroeducational theory and AI technologies in early childhood educational contexts, with particular emphasis on interaction modalities and developmental outcomes.

2. Literature Review

2.1. Foundations of neuroeducation and early childhood development

Neuroeducation has emerged as a pivotal discipline that bridges neuroscience and education to enhance teaching and learning processes through an understanding of brain function and development (Immordino-Yang, 2016). Central to neuroeducation is the concept of brain plasticity, the remarkable capacity of the brain to adapt structurally and functionally in response to experiences, which is especially pronounced during early childhood (Kolb & Whishaw, 2020). This period is characterized by sensitive windows in which exposure to enriched learning environments significantly shapes cognitive, emotional, and social development (Bick & Nelson, 2017).

Key cognitive processes such as attention regulation, working memory, and executive functions develop rapidly in early childhood and form the foundation for complex learning and behaviors (Mareva et al., 2024). Neuroeducational approaches emphasize tailoring educational strategies to leverage these developmental trajectories, fostering optimal neural circuit formation and consolidation (Söderqvist et al., 2012). For example, interventions that support sustained attention and self-regulation have been shown to improve academic outcomes and social competence in young learners (Blair & Raver, 2014).

Moreover, motivation and emotion are deeply intertwined with learning, as the limbic system interacts with cortical networks to modulate memory and attention based on affective states (Immordino-Yang, 2016). Neuroeducation advocates for educational designs that consider emotional engagement as a driver of motivation and cognitive flexibility (Francesetti et al., 2020). Consequently, early childhood education must integrate multisensory, socially interactive, and emotionally supportive experiences to align with neurodevelopmental principles (Van Swieten & Bogacz, 2020).

2.2. Artificial intelligence in education: Concepts and applications

AI has rapidly evolved as a transformative educational technology capable of personalizing instruction and assessment (Li & Yang, 2023). AI encompasses a spectrum of computational techniques, such as approaches based on machine learning, methods of natural language processing, and applications of computer vision, enabling systems to adapt dynamically to learner profiles (Chaddad et al., 2023). Applications in education range from intelligent tutoring systems that provide tailored feedback to adaptive learning platforms that adjust content difficulty in real time (Wei et al., 2022).

In early childhood education, AI-driven tools such as educational robots, voice assistants, and gamified applications offer novel modalities for engagement and skill development (Iffath-Unnisa, 2024). These technologies facilitate multimodal learning experiences that can cater to diverse cognitive and sensory preferences, potentially enhancing attention and motivation (Harry, 2023). Furthermore, the ability of AI to analyze large datasets enables fine-grained monitoring of learner progress and personalized intervention strategies (Bragg et al., 2021).

However, challenges persist regarding the ethical implementation of AI in education, including concerns about data privacy, algorithmic bias, and the risk of depersonalization (Kazim & Koshiyama, 2021). Moreover, the rapid evolution of AI technologies necessitates continuous empirical validation to ensure their efficacy and alignment with developmental and pedagogical principles (Morley et al., 2023).

2.3. Integration of AI within neuroeducational frameworks

The integration of AI within neuroeducational frameworks represents a promising frontier in enhancing personalized learning by aligning technological capabilities with neuroscientific insights (Eager & Brunton, 2023). These technologies may be developed to react to learners' cognitive and emotional states in real time, allowing educational content and pacing to adjust dynamically to maximize neural engagement and improve learning efficiency (Calvo et al., 2014). For example, affective computing enables systems to detect learner emotions such as frustration or boredom, which are critical for modulating attention and motivation in early learners (Cortinas-Lorenzo & Lacey, 2023).

AI-enabled interventions grounded in neurocognitive principles have shown potential in supporting executive functions, including abilities like working memory, self-regulation through inhibitory control, and the capacity for cognitive flexibility, all of which are crucial for early childhood development and academic success (Ram et al., 2021; Wang et al., 2020). These systems can scaffold complex cognitive tasks by breaking them into manageable steps tailored to the child's developmental level, thereby fostering gradual mastery and confidence (Singh & Gothankar, 2021).

Additionally, embodied AI technologies, such as educational robots, provide multisensory and interactive experiences that may better engage the mirror neuron system and social brain networks, promoting social cognition and emotional understanding (Lim, 2024). Such embodied interactions align with the neuroeducational emphasis on social learning and emotional regulation as foundational for cognitive development (Yang, 2022).

Despite these advances, challenges remain in operationalizing neuroeducational principles within AI systems. There is a critical need for interdisciplinary collaboration to ensure that AI design integrates valid neuroscientific models, avoids reductionist approaches, and respects the complexity of early brain development (Su et al., 2023). Rigorous empirical studies are necessary to validate the efficacy of AI applications within this integrative paradigm, ensuring that technological innovation translates into meaningful educational outcomes for young children.

2.4. Empirical studies on AI-enabled neuroeducation in Early childhood

The empirical landscape exploring AI-enabled neuroeducation in early childhood is emerging but still fragmented. Existing research has focused predominantly on isolated aspects, such as the use of educational robots to enhance social skills or adaptive learning platforms that target cognitive functions (Ouyang & Jiao, 2021; Taruchaín-Pozo et al., 2025). Few studies have explicitly linked AI applications with neurocognitive mechanisms or systematically addressed how AI-mediated interventions modulate brain-based learning processes.

Notably, the diversity of AI modalities, ranging from voice assistants to multimodal robotic systems, necessitates nuanced analysis of their differential impacts on attention, memory, executive functions, and socioemotional development (Grinschgl & Neubauer, 2022; Pino-Falconi et al., 2025). Subgroup analyses based on interaction modality have started to reveal promising patterns, with embodied robots showing efficacy in promoting social cognition and engagement, whereas screen-based interfaces appear more suited for cognitive skill acquisition (Zhu & Ren, 2022).

However, many current studies face limitations, including small sample sizes, a lack of longitudinal data, and inconsistent incorporation of neuroscientific frameworks, impeding the generalization and integration of findings. Moreover, ethical considerations specific to early childhood AI applications remain underexplored, raising concerns about attachment, privacy, and equity (Chiu et al., 2023; Su et al., 2023).

This review aims to systematically synthesize these emerging studies, critically evaluate how AI interventions intersect with neuroeducational theory and early developmental needs, and identify gaps to guide future research in this interdisciplinary domain.

3. Research Design and Methodology

Figure 1 represents the methodological flow of the research, which is structured in four main sections: research scope, research framework, PRISMA protocol and conclusions. The first section, Research Scope, describes the fundamentals of the research, which includes a theoretical review and a research design methodology to establish the conceptual basis of the study.

The second section, the research framework, addresses two pillars of research, neuroeducation and AI, highlighting their application in preschool students (< 6 years old). Key concepts from neuroeducation, such as neuroplasticity, metacognition, and neurofeedback, are listed, whereas approaches such as adaptive learning, AI gamification, and educational robotics are included in AI.

The methodological rigor and transparency of this study were upheld through adherence to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines during the study selection and analysis phases. Specifically, the PRISMA protocol, as detailed in the third section, governs the systematic search of scientific databases, including Scopus, PubMed, PsycINFO, and Elsevier, with the article selection process elucidated in the PRISMA flowchart presented in Figure 2.

The central question that directs this systematic review can be stated as: “What is the synergistic role of neuroscience and AI in enhancing early childhood education?”

Finally, the Conclusions section synthesizes the expected results in three fundamental axes, discussion, recommendations, and future lines of research, providing a comprehensive vision of the study.

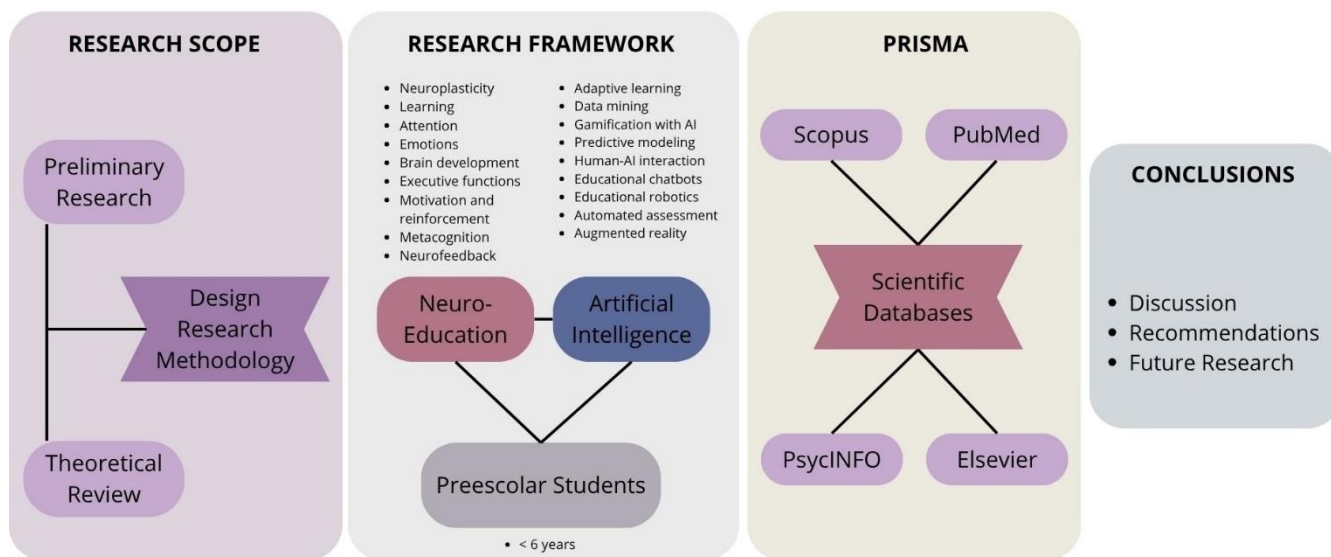


Figure 1 Research methodology flowchart.

3.1. Inclusion and exclusion criteria

To align with the focus on the synergistic relationship between neuroeducation and AI in early childhood, the inclusion criteria were strictly defined as follows: a) peer-reviewed empirical studies published between 2020 and 2025 that explicitly integrate principles of neuroscience, psychology, or cognitive science (collectively neuroeducation) with AI-enabled educational interventions; b) studies targeting children aged 0-8 years, justified by critical neurodevelopmental stages and plasticity during early childhood; and c) articles presenting empirical data on educational outcomes, neurocognitive processes, or developmental impacts facilitated by AI tools designed or applied within a neuroeducational framework.

The exclusion criteria were as follows: a) studies lacking an explicit neuroeducational component or failing to incorporate AI as an active educational technology; b) studies focused on populations outside the specified age range or on theoretical discussions without empirical evidence; and c) gray literature, nonpeer-reviewed articles, and studies without full-text availability.

3.2. Literature search strategy

The literature search was last conducted on March 15, 2025, and was performed in five databases recognized for their relevance in the academic field: Scopus, Web of Science, PsycINFO, Elsevier and PubMed. To ensure comprehensive coverage of the topic, three main research axes were established: artificial intelligence and education, artificial intelligence in early childhood, and early childhood education.

The terms used were structured with Boolean operators, including combinations such as ("Artificial Intelligence") AND ("Early Childhood Education") AND ("Educational Technology"), ("AI-driven Learning") AND ("Young Learners") AND ("Education



Technology"), ("AI-based Learning Tools") AND ("Kindergarten") AND ("Personalized Learning") and ("Artificial Intelligence in Teaching") AND ("Preschoolers") AND ("Interactive Learning").

Additional terms such as ("Artificial Intelligence in Schools") AND ("Digital Education" OR "Educational Technology"), ("Machine Learning in Teaching") AND ("Intelligent Tutoring Systems" OR "Online Learning Platforms") and ("AI-based Education Tools" OR "Chatbots in Education") AND ("Personalized Learning") were also included to cover studies related to the use of artificial intelligence in educational environments.

Finally, specific expressions were considered to address the relationship between artificial intelligence and early childhood, such as ("AI-assisted Learning" OR "Machine Learning for Children") AND ("Preschool Education" OR "Kindergarten Learning"), ("Artificial Intelligence in Early Childhood" OR "AI for Toddlers") AND ("Educational Games" OR "EdTech for Young Learners") and ("AI-powered storytelling" OR "AI-based Learning Toys") AND ("Infants"). In addition, early childhood education-oriented terms such as ("Early Childhood Education" OR "Preschool Teaching") AND ("Digital Learning"), ("Kindergarten Education") AND ("Interactive Learning" OR "Online Learning for Kids") and ("Young Children and Learning") AND ("Adaptive Teaching" OR "EdTech Solutions") were included.

3.3. Selection process

The study selection process was conducted in various stages to ensure the relevance and quality of the articles included in the review. Initially, 735 records were identified in the selected databases. The entire selection process is summarized visually in the PRISMA flowchart (Figure 2).

In the first phase, filtering was conducted by year of publication, excluding 183 records that did not correspond to the period 2020-2025, which reduced the total to 552 articles. A total of 119 records corresponding to gray literature were subsequently eliminated, resulting in a total of 433 studies. A direct access criterion was then applied, which led to the exclusion of 260 articles that were not available in direct access, reducing the number of documents to 173. In the next phase, filtering was conducted by research design, eliminating 40 records that did not meet the established methodological criteria and leaving a total of 133 articles. Finally, duplicate removal was performed, identifying and discarding 42 redundant records, resulting in 91 final papers that were included in the detailed reading phase.

3.4. AI interaction taxonomy and coding

To analyze the diverse formats of AI interaction used in early childhood education, a clear taxonomy was developed to categorize the modalities into four main types:

1. Physically embodied robots: AI systems with tangible, physical robotic forms that children can interact with directly.
2. Screen-based interfaces: AI applications presented via computers, tablets, or smartphones via visual displays and touch interactions.
3. Voice-only interactions: AI systems that communicate solely through auditory channels without a visual or physical interface (e.g., virtual assistants such as Alexa or Siri).
4. Multimodal combinations: systems that integrate two or more of the above interaction formats, offering combined sensory inputs and engagement modes.

Each included study was independently coded according to this taxonomy based on the primary modality of AI interaction evaluated. This classification is presented in the summary tables (see Table 2), enabling a structured subgroup analysis to assess the moderating effects of interaction modality on educational and developmental outcomes.

3.5. Risk of bias assessment

An evaluation of potential bias was carried out using a qualitative approach for all the studies included, applying general criteria adapted from recognized systematic review instruments, such as ROBIS and the Cochrane risk of bias guidelines. The criteria evaluated included appropriateness of the study design, clarity of methodology, sample selection, outcome measurement, and reporting transparency. Owing to heterogeneity in study designs, a simplified risk of bias (Table 1) was created to summarize the assessment.

3.6. Final selection

An exhaustive review was conducted considering the title, abstract, methodology and results of each article. In this phase, the studies were selected according to their relevance and methodological rigor. Of the 91 articles reviewed, 16 corresponded to PsycINFO, of which 8 were selected; 40 came from Scopus, of which 7 were chosen; and 35 belonged to Elsevier, of which 10 were included. Finally, after applying the inclusion criteria and evaluating the eligibility of each study, 18 articles were selected for inclusion in the systematic review. This process made it possible to ensure that the included studies were relevant and of high quality, thus ensuring a solid basis for the analysis of AI in early childhood education.

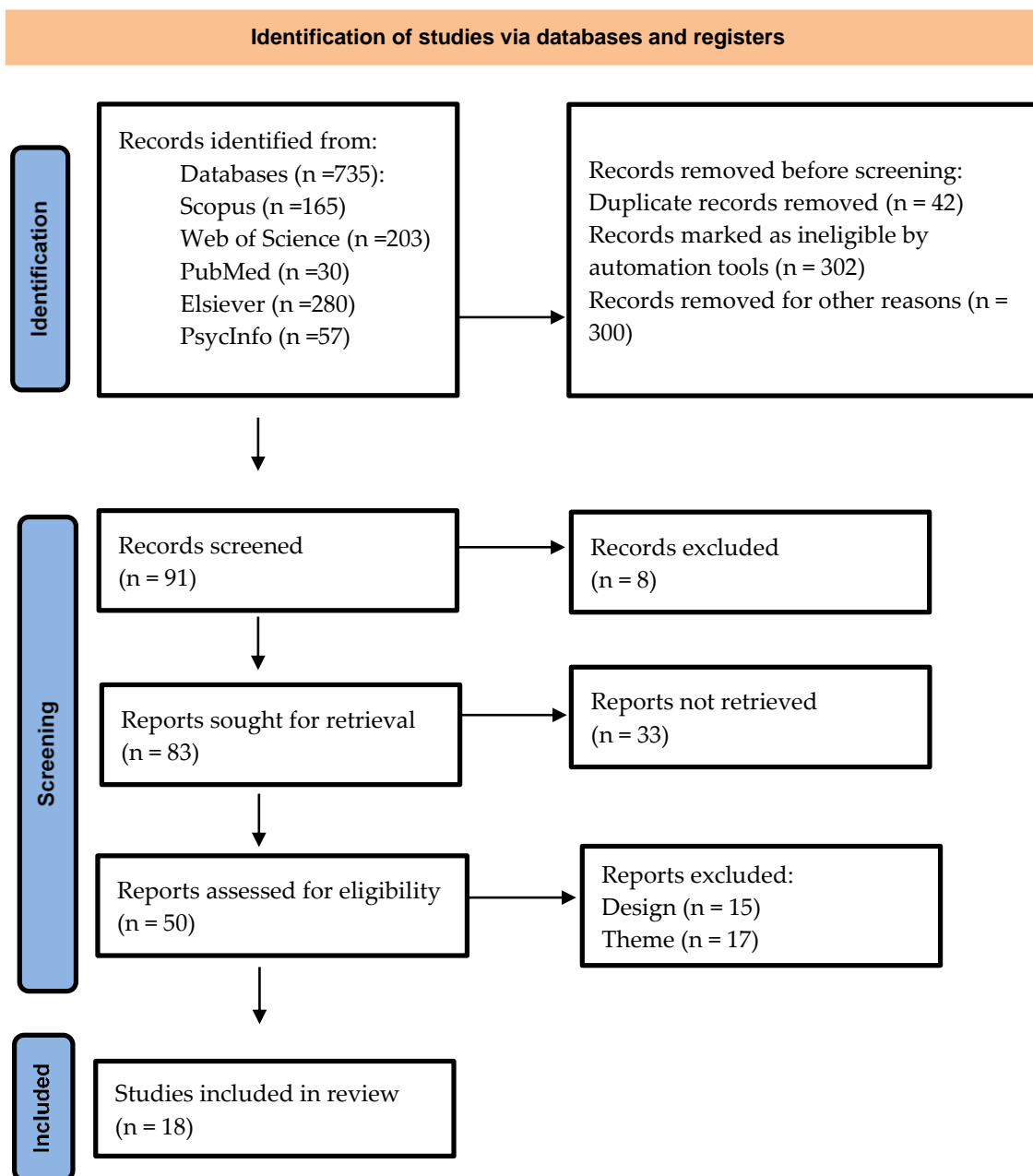


Figure 2 PRISMA Flowchart.

4. Results and Discussion

To ensure the robustness and reliability of the findings synthesized in this systematic review, a qualitative appraisal of bias was conducted across all the studies that were included. This evaluation considered key methodological aspects such as study design appropriateness, clarity of methodology, sample selection, outcome measurement, and reporting transparency. Owing to the heterogeneity of the study designs, a simplified risk of bias summary is presented in Table 1. The assessment provides an overview of the methodological quality of each study, highlighting potential limitations and strengths that inform the interpretation of the review’s results. Most of the analyzed studies showed a risk of bias ranging from low to moderate, which reinforces confidence in the synthesized findings. Limitations in the methodology, including the use of small samples and inconsistencies in outcome measures, were recognized and considered when interpretation of the results.

Table 2 summarizes the characteristics and key findings of the 18 studies included in this review. These studies employed a range of AI technologies in early childhood education settings, targeting cognitive, social, and emotional developmental outcomes. To provide a clearer understanding of the influence of AI interaction formats, each study was classified according to a predefined taxonomy of AI modalities: physically embodied robots, screen-based interfaces, voice-only interactions, and multimodal combinations. This classification facilitated subgroup analyses aimed at exploring the moderating effects of interaction modality on educational and developmental outcomes.



Table 1 Qualitative risk of bias assessment of included studies.

Study	Study design	Sample Selection	Outcome Measurement	Reporting Clarity	Overall Risk of Bias
(Xu, 2023)	Experimental	Adequate	Valid	Clear	Low
(Su & Yang, 2024a)	Intervention	Moderate	Valid	Moderate	Moderate
(Falloon, 2024)	Experimental	Adequate	Valid	Clear	Low
(Gulz et al., 2020)	Experimental	Adequate	Valid	Moderate	Low
(Tarrés-Puertas et al., 2023)	Experimental	Adequate	Valid	Clear	Low
(You & Yang, 2024)	Experimental	Adequate	Valid	Clear	Low
(Su et al., 2024)	Intervention	Adequate	Valid	Clear	Low
(Wang & Yao, 2022)	Experimental	Moderate	Valid	Moderate	Moderate
(Niu, 2022)	Experimental	Adequate	Valid	Clear	Low
(Villegas et al., 2022)	Experimental	Adequate	Valid	Clear	Low
(Aslan et al., 2024)	Exploratory	Moderate	Valid	Moderate	Moderate
(Su & Yang, 2024b)	Review	N/A	N/A	Clear	Low
(Zhao et al., 2023)	Experimental	Adequate	Valid	Clear	Low
(Cheng & Cheng, 2022)	Experimental	Adequate	Valid	Clear	Low
(Zuo et al., 2023)	Experimental	Moderate	Valid	Moderate	Moderate
(Prieto Navarro, 2020)	Experimental	Adequate	Valid	Clear	Low
(Yin, 2022)	Experimental	Moderate	Valid	Moderate	Moderate
(Kanders et al., 2024)	Review	N/A	N/A	Clear	Low

Note: N/A: Not Applicable indicates that the criterion is not relevant for certain studies, such as reviews or qualitative research.

Table 2 List of selected research articles.

Study	Study Title	Participants/Intervention	Conclusions (synopsis)
(Xu, 2023)	Talking with machines: Can conversational technologies serve as children's social partners?	Children aged 3 to 8 interact with virtual assistants such as Siri and Alexa, connected toys, and social robots to assess their cognitive and social development. [Modality 3]	The interactions indicate that these social companions allow for learning like that which occurs with humans. Children perceive them as social and emotional entities, and some even attribute human capacities to them.
(Su & Yang, 2024a)	AI literacy curriculum and its relation to children's perceptions of robots and attitudes toward engineering and science: An intervention study in early childhood education	AI4KG (AI for Kindergarten) interactive educational program to teach AI through tools such as "Teachable Machine", "AI for Oceans", and "Quick, Draw!" to children aged 3 to 5 years old from a kindergarten in Hong Kong. [Modality 2]	The AI4KG program improves children's perceptions of AI and robots, with an increase in their knowledge and attitude toward technology.
(Falloon, 2024)	Advancing young students' computational thinking: An investigation of structured curriculum in early years primary schooling	Six-year-olds learn computational thinking (CT) by coding programmable robots (Blue-bots and an iPad app). [Modality 1 and 2]	Improvements in skills such as sequencing, algorithm creation, and problem solving, with higher thinking development.
(Gulz et al., 2020)	Preschoolers' Understanding of a Teachable Agent-Based Game in Early Mathematics as Reflected in their Gaze Behaviors – an Experimental Study	Evaluation of children's mathematical comprehension through the "Magical Garden" game based on teachable agents, their visual behaviors were measured by eye-tracking during five rounds. [Modality 2]	Children who had a better understanding of number concepts showed more accurate visual patterns and correctly anticipated tasks.
(Tarrés-Puertas et al., 2023)	Child–Robot Interactions Using Educational Robots: An Ethical and Inclusive Perspective	The intervention consisted of educational activities for 212 students (64 children aged 3 to 6 years) using the Qui-Bot family of robots (Lab Qui-Bot, Lab2 Qui-Bot, MultiArm Qui-Bot, and	Qui-Bot robots capture students' interest and facilitate the learning of scientific concepts in an inclusive way



		3D Qui-Bot) to integrate STEM competencies, gender equality and inclusion. [Modality 1]	
(You & Yang, 2024)	Evaluation of the effectiveness of robot-assisted teaching in the training room in preschool education	Evaluation of robotic-assisted teaching based on models of coordinate transformation, speed movement, odometry, and visual and auditory recognition in 30 children, compared to traditional methods. [Modality 1].	Significant improvement in learning, linguistic expression, and cooperation, with high satisfaction in the use of robots
(Su et al., 2024)	Early artificial intelligence education: Effects of cooperative play and direct instruction on kindergarteners' computational thinking, sequencing, self-regulation, and theory of mind skills	Use of AI robots (UBTECH and robot dogs) in cooperative games and direct teaching, to improve computational thinking, sequencing, self-regulation, and theory of mind skills to 90 kindergarteners (5-6 years old). [Modality 1].	Significant improvement in computational thinking, sequencing, and self-regulation, with cooperative play favoring theory of mind.
(Wang & Yao, 2022)	A Genetic Neural Net Model for the Relationship between Pre-School and Attention in Early Childhood	Using a Genetic Neural Network Combined with Attention Mechanisms and Deep Learning in Rule Games in Preschoolers. [Modality 2]	Rule-play intervention significantly improves sustained and selective attention, especially in girls.
(Niu, 2022)	An artificial intelligence method for comprehensive evaluation of preschool education quality	Use of a Fuzzy Neural Network (FNN) model and Analytical Hierarchy Process (AHP) to evaluate educational quality in preschoolers. [Modality 2]	The FNN model shows high accuracy in the evaluation of educational quality, improving the speed of convergence and accuracy.
(Villegas et al., 2022)	Assistance System for the Teaching of Natural Numbers to Preschool Children with the Use of Artificial Intelligence Algorithms	AI-assisted pedagogical system to teach natural numbers from 0 to 9 to preschoolers. The system focused on image recognition. [Modality 2].	Improved identification and writing of numbers, with more stable learning compared to the traditional method.
(Aslan et al., 2024)	Immersive multimodal pedagogical conversational artificial intelligence for early childhood education: An exploratory case study in the wild	Kid Space, an interactive learning system for 14 preschoolers in the U.S. to improve the academic performance of first-grade students. [Modality 4].	Significant improvements in mathematical performance, influenced by interaction with the system and its design
(Su & Yang, 2024b)	Artificial Intelligence and Robotics for Young Children: Redeveloping the Five Big Ideas Framework	Using Educational Robots to Teach the Five Key Concepts of AI and Promote Literacy to Young Children. [Modality 1].	Robot activities foster curiosity and basic understanding of AI, promoting interactive learning.
(Zhao et al., 2023)	Optimization of the game improvement and data analysis model for the early childhood education major via deep learning	Implementation of a Game Improvement and Data Analysis (GIADA) model based on deep learning (DL) and convolutional neural network (CNN) techniques. [Modality 2]	The DL-CNN model improves the accuracy of data analysis, reaching a range of 81% to 93%, compared to 42%-68% in the basic version
(Cheng & Cheng, 2022)	Empirical Analysis of Early Childhood Enlightenment Education Using Neural Network	Intelligent search system for big data in early childhood education, based on deep neural networks (DNN). The public dataset of the Ministry of Education and the dataset of Taylor's University in Malaysia (NUS-WIDE) were used. [Modality 2].	A significant improvement in search accuracy was observed, with a 15.6% increase in the average accuracy mean (MAP) value in the public dataset and a 20.6% increase in the NUS-WIDE set
(Zuo et al., 2023)	The development of robotics courses for young children under vector space mode	The study involved the development of a robotics course for young children from 38 kindergartens in Baoji City. AI and the Vector	The results show that only approximately 24% of kindergartens offer robotics

		Space Model (VSM) were used to promote thinking, manipulation, and creativity skills. [Modality 1].	courses and that 70.14% of teachers support the implementation of these courses. The VSM surpassed the traditional TF-IDF method, reaching accuracy, recall and F1 values above 85%. Multimodal teaching improves children's participation and understanding, reducing the time spent on repetitive assessments.
(Tuo & Long, 2022)	Construction and Application of a Human-Computer Collaborative Multimodal Practice Teaching Model for Preschool Education	Multimodal model and nine Gagné instructional events for the teaching of English in preschoolers, using the EasyDotWise System and robots. [Modality 4]	Multimodal teaching improves children's participation and understanding, reducing the time spent on repetitive assessments.
(Yin, 2022)	Personalized Hybrid Education Framework Based on Neuroevolution Methodologies	Automated student clustering system based on neuroevolution and heuristic optimization GsONG (Growing Semi-Organizing Neural Gas). [Modality 2]	The GsONG model improves personalized education, allowing an adapted assignment of content to each student.
(Kanders et al., 2024)	Perspectives on the impact of generative AI on early-childhood development and education	Analysis of the impact of generative artificial intelligence (GAI) on teaching and supporting families and educators in early childhood education, using language models and conversational chatbots. [Modality 3]	The need to rigorously evaluate generative AI tools and their effectiveness in children's learning is underlined.

Note: AI Interaction Modality taxonomy codes: 1 = Physically embodied robots; 2 = Screen-based interfaces; 3 = Voice-only interactions; 4 = Multimodal combinations.

The empirical studies selected for this systematic review reveal four principal thematic axes concerning the integration of AI within neuroeducational frameworks in early childhood: (1) the development of cognitive and computational skills; (2) the stimulation of executive functions and attention; (3) personalization and educational quality assessment; and (4) multimodal integration and emerging ethical concerns.

4.1. Development of cognitive, computational and STEM competencies

Several studies have contributed to the understanding of how AI technologies support the development of foundational cognitive and technological literacies in early childhood. Falloon (2024) reported that programming robots strengthens sequencing and problem-solving skills in early learners. Su et al. (2024) reported that robot-assisted activities enhance computational thinking, self-regulation, and theory of mind.

Su & Yang (2024a) reported that the AI4KG program improved children's attitudes toward AI and fostered early engagement with technology. In a complementary contribution, Su & Yang (2024b) emphasize that educational robotics can be effectively employed to introduce foundational AI principles, fostering curiosity and interactive learning in early childhood. Finally, Tarrés-Puertas et al. (2023) emphasize the inclusive potential of AI-mediated STEM instruction with the QuiBot family of educational robots, which integrate ethical considerations such as gender equity while promoting scientific literacy. These studies collectively underscore the capacity of AI-driven tools to support early cognitive development and identity formation within STEM domains.

4.2. Stimulation of attention, language and socioemotional development

A second group of studies explores the role of AI in modulating attention, enhancing language skills, and supporting social cognition, capacities deeply rooted in neurodevelopmental processes. Xu (2023) revealed that children perceive AI voice assistants as social agents, suggesting potential for socioemotional learning.

You & Yang (2024) observed improvements in language use and cooperation in classrooms via robot-assisted instruction. Wang & Yao (2022) focus on attentional development and report that preschoolers who participate in AI-enabled rule-based games, developed via genetic neural networks, show marked improvements in sustained and selective attention, particularly among girls. These findings suggest that targeted AI interventions can support key executive functions that underpin later academic achievement and self-regulatory competence.

4.3. Personalized learning and automated educational assessment

The integration of AI for personalized instruction and evaluation is illustrated by a series of studies that leverage algorithmic modeling to adapt learning to the individual developmental profiles of young children. Niu (2022) presented a fuzzy

neural network that increases accuracy in assessing preschool learning outcomes, offering a data-driven approach for continuous pedagogical monitoring.

Villegas et al. (2022) reported that an AI-assisted system improves number recognition and writing skills. Cheng & Cheng (2022) reported enhanced data analysis performance via deep neural networks in educational datasets. Similarly, Yin (2022) introduced a neuroevolutionary framework (GsONG) for clustering students by learning profiles, enabling tailored content delivery.

Finally, Zuo et al. (2023) implemented a robotics course supported by vector space modeling, showing strong teacher support and positive learning outcomes. Collectively, these works exemplify how AI can operationalize personalized learning and enable formative assessment in ways that are congruent with neurodevelopmental diversity and learning variability.

4.4. Multimodal integration and ethical-pedagogical implications

The final thematic cluster addresses both the technological sophistication of multimodal AI systems and the emerging ethical considerations surrounding their use in early educational settings. Aslan et al. (2024) examine “Kid space,” a multimodal AI learning system that reports cognitive gains from the use of a multimodal AI system that combines embodied and conversational interactions.

Tuo & Long (2022) highlight how AI-supported multimodal teaching improves participation and reduces instructional redundancy. Their findings suggest that such systems can increase participation and comprehension while reducing instructional redundancy—benefits that resonate with neuroeducational principles.

Finally, Kanders et al. (2024) call for critical evaluation of generative AI tools, noting risks related to emotional attachment, privacy, and developmental appropriateness. These contributions emphasize that while AI holds promise as a transformative educational agent, its integration must be guided by principles of developmental appropriateness, ethical responsibility, and pedagogical coherence.

4.5. Theoretical and practical implications

These findings underscore the importance of interaction modality as a significant moderating factor influencing the effectiveness of AI-based interventions in early childhood education. The physical embodiment of AI systems appears to enhance children's perceptions of agency and social presence, thereby contributing to improved socioemotional learning outcomes. This insight has meaningful implications for educators, researchers, and technology developers seeking to design and implement AI tools that align with developmental needs and optimize learning experiences.

4.6. Ethical considerations

Finally, ethical considerations vary according to AI modality. Embodied robots may foster emotional attachment and parasocial relationships, necessitating careful monitoring to prevent emotional dependency. In contrast, voice-only and screen-based systems raise distinct privacy and data security concerns. Addressing these modality-specific ethical challenges is essential for guaranteeing that AI technologies are incorporated in a secure and responsible manner within early childhood educational contexts.

5. Final Considerations

Neuroeducation, in conjunction with AI, represents a transformative paradigm in early childhood education by harnessing the inherent plasticity of the brain to optimize learning experiences. The evidence synthesized in this review shows that conversational and interactive systems can function as social learning partners, enhance emotional engagement and support the development of language skills. Embodied AI technologies contribute to the strengthening of computational thinking, sequencing, and problem-solving abilities in young learners, while also fostering inclusion and equity in STEM education.

Algorithmic approaches provide valuable tools for the adaptive assessment of preschool learning outcomes. By dynamically analyzing individual performance profiles, these models make it possible to personalize instruction in ways that align with each child's developmental trajectory, thus reinforcing the neuroeducational principle of differentiated learning.

The integration of AI in early education also requires careful ethical consideration. It is essential to ensure that children's emotional well-being, privacy, and the integrity of human relationships are safeguarded. Responsible implementation calls for collaboration among educators, technologists, and policymakers so that AI applications remain developmentally appropriate and equitable.

From a practical perspective, teacher training should combine neuroscientific knowledge with AI-mediated pedagogical strategies, enabling educators to apply these tools effectively while maintaining a child-centered approach. At the same time, technology developers must design with attention to motivation, attention, and socioemotional engagement. Educational policies should incorporate evidence-based frameworks that promote ethical, inclusive, and developmentally appropriate uses of AI in early childhood settings.

Despite the promising results, this review also reveals certain limitations, such as heterogeneous study designs, small sample sizes, and the predominance of short-term interventions, which restrict the generalizability of findings. Future studies should prioritize longitudinal research with larger and more diverse samples, using standardized outcome measures. In addition, the taxonomy presented here can serve as a foundation for systematically examining the specific effects of different AI interaction modalities.

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Ethical Considerations

Not applicable.

Conflict of Interest

The authors declare that there are no conflicts of interest.

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