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The Application of Artificial Intelligence Technology in Early Childhood Language Development

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Abstract

Artificial intelligence (AI) tools are becoming more and more prevalent in early childhood education, but their effects on language development and the pedagogical settings in which they work best have not yet been thoroughly examined. This review takes a sociocultural stance and uses the Zone of Proximal Development (ZPD) theory to analyze AI-assisted language learning. Sixteen peer-reviewed empirical papers representing study contexts from various nations and regions that were published since 2021 and indexed in Web of Science (WoS) and Scopus were combined. Three types of AI tools are the main focus of current research: speech-based systems, social robots, and conversational agents/chatbots.The results show that children's linguistic engagement and participation during learning activities, story comprehension, and vocabulary acquisition all consistently gain from AI. According to ZPD, AI works best when it serves as a kind of scaffolding, facilitating interactional processes like dialogic prompting, instant feedback, and cooperative attention, and when these interactions are coordinated with kids' developmental needs under the direction of educators or caregivers. Overall, AI technologies show great promise for improving early language development when they are developed and used to supplement rather than replace socially mediated education. To support theory-informed and evidence-based integration of AI in early childhood language education, future research should make more use of longitudinal designs, expand validation across cross-cultural and multilingual contexts, and more precisely define scaffolding mechanisms.

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Introduction

The Rapid Development of Artificial Intelligence Technology and Its Application in Education

With the fast-paced growth of Artificial Intelligence (AI), the education sector is undergoing a significant transformation, bringing both new opportunities and emerging challenges (UNESCO, 2023; UNESCO, n.d.). The use of AI has been increasingly associated with supporting teaching and learning, enabling more personalized learning pathways, and strengthening aspects of educational management (Garzón et al., 2025; Hariyanto, 2025). These developments are particularly relevant to early language development in early childhood, where learning is highly sensitive to interaction quality and the learning context.

Smart AI teaching assistants have also been integrated into virtual laboratory environments to provide more immersive and interactive learning experiences (Cheon & Kang, 2025). In addition, AI can support customized learning by adapting educational content and instructional support to individual learners' needs, which may enhance learning effectiveness and performance (Garzón et al., 2025; Hariyanto, 2025).

AI finds applications in higher education to proactively control teaching resources and adopt efficient individual teaching plans and improve the overall level of education (Wang, 2024; Na, 2024). The integration of AI in teaching practices can produce an efficient and more human-centered learning setting along with the use of traditional teaching practices. This strategy would make sure that AI is an assistant tool and not a replacement of human teachers (Na, 2024).

The implementation and planning should be done carefully to take advantage of the benefits of AI as much as possible and reduce the effects that are negative. This involves tackling issues related to ethics and providing a fair access to AI technology (Na, 2024; Zhang and Deng, 2022).

Despite the potential AI can bring changes in the field of education, it is necessary to moderate the changes in technology with the human side to preserve the quality and integrity of education. The problem of fair access and ethical concerns addressing need to be addressed to maximize the potential of AI.

The incorporation of the AI technology in the education sphere is transforming the ordinary educational process and improving the process of learning. The use of AI applications like individualized learning programs, robotic assessment systems, and intelligent learning platforms have been really effective in addressing the various educational requirements. This change is advocated by a great number of research papers pointing to the fact that AI-based educational devices have greatly increased student engagement and study results. The AI systems adapt to personal learning preferences and present specific resources and assistance, which makes students more engaged and informed (Jin Rong, 2025; Kaur et al., 2024).The systems provide real-time feedback and guidance and enable students to learn more successfully in complex subjects (Kaur et al., 2024; Hanafiah et al., 2025). AI compiles huge volumes of study information, which assists in developing methods of teaching and learning (Cheng Yuan, 2025; Rishwinder et al., 2024).

Although AI has been extensively used during the language learning of children, there is no comparative research on its strengths and weaknesses in various countries and cultural backgrounds. Majority of the current studies conducted deals only with AI application in one country ignoring the variation in its influence to language growth of children in different educational settings and other cultures. Also, although the positive aspects of AI, including personalized learning and feedback in real-time have been proven, the negative possibilities, including excessive dependence on technology, privacy issues, and diversity restrictions, are not researched in a structured manner. The study presented is meant to address this gap by researching the benefits and drawbacks of AI in language teaching among children by cross-country comparisons.

The Importance of Early Childhood Language Development

The early language language development in early childhood is essential because it forms the basis of cognitive, social and emotional developments. The abilities that children develop during this vital stage are critical towards proper communication and learning as these skills are of language. The need to create an inclusive linguistic environment and use effective teaching approaches cannot be ignored because it has a great influence on the overall development of the child. Some of the foremost points depicting the significance of language development at early childhood are given below.

Language proficiency is strongly connected with cognitive processes, and the language development at the early ages can foretell the success in the further studies (Xu, 2025). Children with the good language experiences have better problem solving and critical thinking abilities (Morrow, 2005).

Communication facilitates social exchange and children learn how to develop interpersonal relationships with each other and adults (Popescu and Cenușe, 2023). As well, emotional expression can be ensured within the context of language development, as children can express their emotions and needs, and such aspects are essential in regard to emotional self-control (Khuong, 2025).

The reports have indicated that cultural levels of parents have a close relationship with the provision of language stimulation and that parents have a vital role of supporting language development (Bhilbina et al., 2025). Interagency of parents, teachers, and healthcare professionals is critical in the development of a language-rich supportive environment (Bhilbina et al., 2025).

Language development during the early childhood is a component that is central to cognitive, social and emotional development. Early language skills acquisition is an important predictor of academic success and critical thinking skills. Language communication is effective in that it fosters socialization as well as emotional expression and control.

Despite the potential in the field of AI in supporting language education, the research involving a contrast between its effects on language learning in early childhood in other countries and cultures has not been conducted. The majority of research is devoted to the particular uses of AI in language learning within a particular educational setting without considering the fact that its use in various educational systems is different. Moreover, though the benefits of AI, including personalized learning and real-time feedback, have been identified, the use of AI has its potential negative effects, including cultural biases, excessive use of technologies, and privacy, which also have not been sufficiently considered especially regarding young learners. This gap in the literature calls for a comparative study to evaluate how AI can support language development in early childhood across various cultural and educational settings, as well as to critically assess both its benefits and limitations.

Research Questions

1. How have AI technologies been applied to support early childhood language development, and what language learning outcomes have been reported across empirical studies?
2. What strengths and limitations of AI-supported language learning in early childhood emerge from existing research when interpreted through a sociocultural (ZPD) perspective?

Research Objectives:

To summarize the current research stage of AI technology in the language development of children, assess the impact of its application, discuss the existing challenges, and find the future research directions. Make recommendations practical with respect to using AI in early childhood education and language teaching to benefit educators and policymakers.

Theoretical framework

Activity theory originated from Vygotsky's (1978) triad model of subject, object, and tools for psychological development, which was expanded by Engeström (1987) to include contextual elements of rules, community and division of labour in addition to subject.The six elements compose the unit of analysis, in the socio-historical context of both individual and collective levels (Koszalka & Wu, 2004).

Activity theory provides an analytical framework for analysing the need, activity, and outcome of the technology-supported learning environment (Jonassen & Rohrer-Murphy, 1999; Rambe, 2012). The subject is an individual or a group participating in the activity. The object is the motive or goal driving the subject to take the activity. The tools refer to either material or psychology artefacts mediating the relationship between the subject and object. The rules are the norms the subject follows and decides the cooperation between the participants. The division of labour is the organisation of the activity and distribution of responsibility among the participants.

The community refers to the social group mediating the interaction between each element (Zheng et al., 2020). Research using activity theory in analysing educational technology has increased (Hite & Thompson, 2019; Kaptelinin & Nardi, 2006; Zheng et al., 2020), especially in game-based learning (Carvalho et al., 2015) and the use of social media in learning (Rambe, 2012). Researchers argued that activity theory can "address the challenge of studying the interaction between technology and actors" (Karanasios et al., 2018; p. 439). Activity theory has been used as the conceptual framework in the literature review of mobile assisted language learning for reading (Lin et al., 2019).

AI as a fast-developing technology has been used in language education. However, to date there has been no systematic review of the empirical research on AIsupported language learning. In addition to the aspects illustrated in the technology-based learning model in the Liang et al. (2021) review, this review used activity theory as the theoretical framework. The aim was to show the interaction between the subject, AI technology and the objects, and analyse the process of human interaction with technology via the collective activity in which the subject participates (Kaptelinin & Nardi, 2006). The strengths of using activity theory as an analytical framework include: (1) it can illustrate the boundary between the artefact/tool and the subject in constructing consciousness; (2) it can illustrate the materialisation of consciousness from socially mediated activities; and (3) it can show the transcendence from individual to collective activities for analysing the object-oriented, tool-mediated activity system (Rambe, 2012).

Methodology

This systematic review follows the principles of PRISMA. The PRISMA methodology includes conducting systematic searches in the Scopus and Web of Science databases, establishing inclusion and exclusion criteria, implementing the study selection process (identification, screening, and eligibility), and extracting and analysing data from the included studies. As highlighted by Higgins et al. (2019), systematic reviews help clarify the foundations on which subsequent studies build, determine the extent of current knowledge in the field, and synthesise the value and insights provided by existing research, thereby supporting more accurate and evidence-informed decision-making.

The authors also note that PRISMA offers three distinct advantages (Sierra-Correa & Kintz, 2015): (1) it enables the formulation of clear and precise research questions that define the scope of the systematic study; (2) it specifies inclusion and exclusion criteria; and (3) it facilitates the systematic exploration of large scientific literature databases within defined timeframes. Guided by PRISMA, this paper can rigorously identify and integrate empirical evidence on the use of AI to support language development and language learning in children aged six years and under.

Search Strategy

This study follows the PRISMA 2020 guidelines for conducting a systematic literature review. To ensure comprehensive and rigorous retrieval, the study conducts systematic searches in two major international databases: Web of Science (WoS) Core Collection and Scopus.

- Databases: Web of Science, Scopus
- Search Date: October 1, 2025 (fixed time point)
- Literature Year Limit: 2021-2025
- Literature Type Limit: Article
- Language Requirement: English

Data Integration and De-duplication

- A total of 264 articles were retrieved from Web of Science and 66 articles from Scopus. After merging the two sets of literature, automatic and manual de-duplication was performed using EndNote / Zotero.
- Total initial articles: 264 + 66 = 330 articles
- Articles after de-duplication: 12 articles

Table 1: The keywords and strategy to search for information

Database	Search Query	Initial Results
Web of Science	TS=((“artificial intelligence” OR “AI” OR “AI-assisted” OR “AI-supported” OR “educational robot” OR “robot-assisted” OR “conversational agent” OR “chatbot” OR “speech recognition” OR “intelligent system”) AND (“early childhood” OR “early childhood education” OR preschool OR “pre-school” OR kindergarten OR “young children”) AND (“language development” OR “language acquisition” OR “oral language” OR vocabulary OR “early literacy” OR “literacy development”)) NOT TS=(adult OR university OR college OR adolescence)	264 articles
Scopus	TITLE-ABS-KEY((“artificial intelligence” OR “AI” OR “AI-assisted” OR “AI-supported” OR “educational robot” OR “robot-assisted” OR “conversational agent” OR “chatbot” OR “speech recognition” OR “intelligent system”) AND (“early childhood” OR “early childhood education” OR preschool OR “pre-school” OR kindergarten OR “young children”) AND (“language development” OR “language acquisition” OR “oral language” OR vocabulary OR “early literacy” OR “literacy development”))	66 articles

Record Selection Process:

The PRISMA flowchart is used to record the selection process, showing the number of articles at each stage, as follows:

- Total number of articles initially searched: 330 (including WoS and SCOPUS articles)
- Number of articles after de-duplication: 318
- Number of articles selected initially: Based on the inclusion criteria and quality assessment, the articles to be excluded are determined.
- Number of final articles selected: All articles that meet the inclusion criteria.

Quality Assessment and Analysis:

- Quality assessment was conducted for the remaining articles, selecting those that represent key characteristics and relevance for final analysis.

Inclusion Criteria

The literature must meet the following criteria to be included:

1. Study subjects: The research must focus on preschool children (ages 3–6), including those in preschool, kindergarten, and early childhood education stages.
2. Research topic: The study must align with the theme of this review, specifically focusing on the application of AI technology in language development, including vocabulary, oral expression, language comprehension, early literacy, etc.
3. Involvement of AI technology: The research must involve AI technologies such as educational robots, chatbots, speech recognition systems, large language model (LLM)-enhanced agents, AI-assisted learning, intelligent systems, etc.
4. Research type: Only peer-reviewed journal articles are included, covering empirical studies, mixed-methods research, experimental research, and qualitative research.
5. Publication time: The research must be published between 2021 and 2025 to ensure it reflects the latest developments in AI technology.
6. Language: The literature must be in English.

Exclusion Criteria

The literature will be excluded if it meets any of the following conditions:

Irrelevant study subjects:

- Primary and secondary school students, university students, or adults
- Medical/special needs/clinical populations

- Studies that do not clearly involve children aged 3–6 years

Irrelevant topics:
- Does not involve artificial intelligence technology
- Does not focus on language development (e.g., topics like mathematics, science, ICT literacy, etc.)

Inappropriate document types:

Exclude: Review articles, conference papers, books, book chapters, opinion articles, reports, and theses.
- Non-English or not published between 2021 and 2025
- Insufficient research methods or data:
- No empirical data, unclear descriptions, or results that cannot be extracted.

Unclear AI involvement or only traditional digital tools used:
- Use of simple tablet teaching, educational technology devices, or software without intelligent features.

Screening Process

The literature selection process consists of three steps:
- Title and Abstract Screening:
  Initially, exclude irrelevant literature based on inclusion/exclusion criteria.

Full-Text Screening:
- Read the full text of the remaining literature and further exclude studies that do not meet the criteria.

Final Inclusion of Literature:
- Include the studies that meet the criteria for qualitative or quantitative synthesis.

Data Extraction

For the studies finally included, the following information will be extracted:
- Authors and Year
- Country
- Research Design and Methods
- Main Results and Conclusions

Result

This image illustrates the process of literature screening. Twenty-seven articles were studied and examined. Literature relevant to the research was appropriately identified by reviewing article abstracts and then (in-depth) reading the full text. Content analysis identified 16 articles on the application and impact of educational laws in early childhood education management. Analysis was conducted based on similarity or relevance (Adams et al., 2021).

The inclusion and exclusion criteria determined the selection of the articles. In this study, a total of 16 articles met the inclusion criteria and were evaluated and analyzed. This study employs content analysis to examine the content and identify its features, themes, or patterns. The coding scheme is built to specify the process of extraction of relevant data of the literature, which is in line with the research questions (Elo and Kyngas, 2008; Sanusi et al., 2023). The coding scheme has the following components; article title, author(s), research methodology, year, and research findings. Figure 1 below is a PRISMA diagram that describes the inclusion and exclusion which occurs when extracting the data.

The process of literature screening is depicted in this table. There were 16 articles under study and analysis. The literature was assessed appropriately to identify the area of relevance, through reviews of the abstracts of articles and then a thorough reading of the text was done. The content analysis received 16 articles involving the use of AI in the learning of language among children. Similarity or relevancy was used as a factor to conduct the analysis (Adams et al., 2021). The study entails different countries, and the data retrieved comprises the following: the authors, the year taken to conduct the research, the research methodology, the key findings, and the conclusions.

The data analysis was undertaken in terms of themes (Boyatzis, 1998; Braun and Clarke, 2012). Each of the studied works was coded and classified systematically, depending on their focus and methodological peculiarities. In the beginning of the studies, an independent coding by the first two authors has been utilized, where recurrent patterns

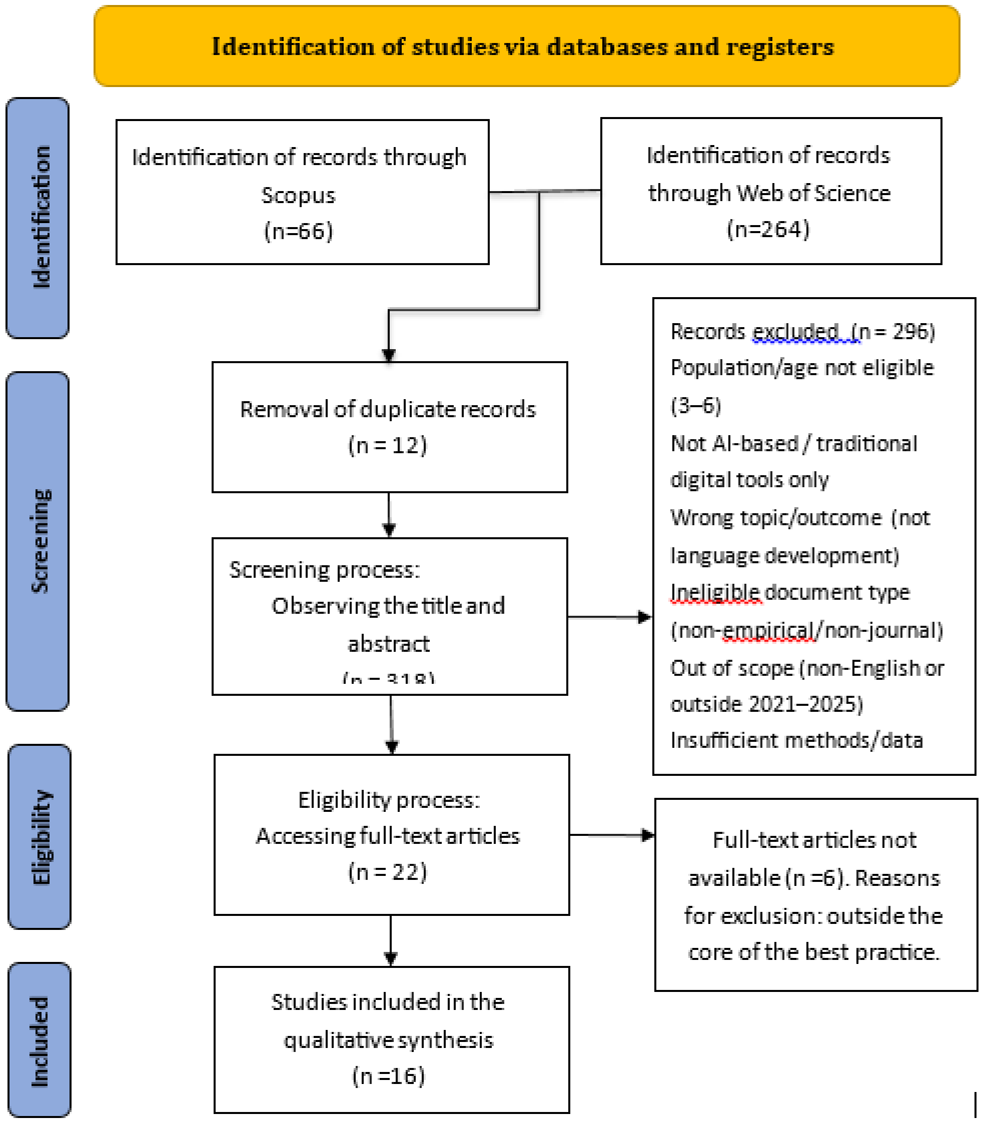

Fig. 1: Study flow diagram

Souce: Moher et al., 2015

in the goals, results, and environment of the research were determined through content analysis. Similar codes were subordinated into broad themes, which were perfected with recurrent discussions until an agreement was achieved. This procedure was meant to provide uniformity and clarity in the synthesis of qualitative evidence (Thomas and Harden, 2008) and arrived at the four major categories of the analytic category, they include; (1) effects of artificial intelligence in early childhood language learning, (2) the role of robotics in supporting early childhood learning, (3) issues of educational fairness with implementation of technology, and (4) the interactional learning and teacher support. These groups formed the format of the findings and discussion sections, which helped to find the patterns, contrast, and correlation between artificial intelligence and language learning in children.

Table 2: The characteristics of the selected articles

Author-Year	Country	AI type	Target language skills	Outcomes (reported)	Design	ZPD/Scaffolding mechanism coded (codes + evidence phrase)
Xiao et al., 2025	China	Bilingual conversational agent (LLM interactive e-book)	Multilingual output; general language skills	Output & interaction; skill development support	Qualitative	S4 "bilingual conversational interaction to elicit output"; S2 "multilingual/ personalized interactive e-book" (needs verification)
Güneş, 2025	Indonesia	AI-supported storytelling & game-based teaching (AI unspecified)	Speaking; motivation	Speaking & motivation ; engagement	Qualitative	S6 "storytelling/game activity script"; S2 "personalized learning claim" (needs verification)
Jouen et al., 2025	Japan	Social robots (interactive vs non-interactive)	Vocabulary	Interactive robot > non-interactive; eye-tracking supports social cue effects	Quantitative	S3 "timely social cues (eye-gaze/attention)"; S4 "interactive robot-led word learning"
Roldan-Cardona et al., 2025	Spain	AI-enhanced teaching (details unspecified)	NR (language implied)	Motivation/ engagement ; no sig. diff; personalization claimed	Mixed	S2 "personalized learning pathway claim" (needs verification); NR "mechanism not specified in summary"
Vargas-Díaz et al., 2025	NR	Voice-agent shared-reading system (TaleMate)	Participation; story recall	Participation & recall ; parents: shared reading enhanced	Qualitative	S5 "parent-child co-reading supported by system"; S4 "interactivity to sustain dialogic engagement"
Leech et al., 2025	USA	Conversational agent (CA) for reading	Early literacy interaction; child responses	Parent-child talk ~2×; child responses ; no sig. diff	Quantitative	S5 "adult-child talk amplified during CA reading"; S4 "CA prompts eliciting child language responses" (prompt type needs verification)
Cheng et al., 2024	China	Chatbot conversational reading support	Story comprehension; word learning	Comparable to human partner; effect moderated by child language ability	Quantitative	S4 "chatbot as dialogic reading partner"; S2 "effects varied by child language ability (learner-level fit)"
Cho & Yim, 2024	Korea	AI-generated stories	Vocabulary	Comparable vocab gains vs traditional; engagement	Quantitative	S6 "AI-generated story content as scaffold"; NR "interactive prompting/ feedback not specified"

Author-Year	Country	AI type	Target language skills	Outcomes (reported)	Design	ZPD/Scaffolding mechanism coded (codes + evidence phrase)
Xu, Yu, Ober & Warschauer, 2022	USA	Conversational agents for dialogic reading	Story comprehension; vocalization	Vocalization ; comprehension	Quantitative	S4 “dialogic reading via CA increases vocalization”; S1 “questioning/prompting features” (needs verification)
Xu, Y.; Wang; Warschauer, 2021	USA	Conversational agents in adult-child interaction	Comprehension; participation; vocabulary diversity	CA: comprehension/participation □; adults: vocab diversity/topic relevance	Quantitative	S4 “CA-led questioning supports participation”; S1 “differentiated response patterns for demanding questions” (needs verification)
van den Berghe et al., 2021	Netherlands	Robot vocabulary training + gestures	Vocabulary	Differential effects by learner ability/memory; some benefit more from robot	Quantitative	S3 “robot gestures as attentional/social scaffold”; S2 “benefits differed by baseline vocabulary/memory (learner-level sensitivity)”
Berrezueta-Guzman & Dolón-Poza, 2025	Germany	Robot assistants	Vocabulary	+23% vocab vs traditional (reported); engagement	Quantitative	S3 “robot-assisted engagement (social presence)” (needs verification); NR “specific cues/prompting not specified”
Yuan, Dong & Zheng, 2025	China	Chatbot shared reading (self-directed vs controlled support)	Language skills via shared reading	Typical readers: self-directed > controlled; weaker readers: controlled > self-directed	Quantitative	S2 “support mode matched to learner needs”; S4 “chatbot-guided shared reading dialogue”; S1 “controlled support implies contingent prompts” (needs verification)
Yin et al., 2024	China	Social robot behaviors (friendly/interactive)	L2 learning	Motivation ; language outcomes	Quantitative	S3 “friendly/interactive robot behaviors supporting engagement”; S4 “interactive exchanges during L2 learning” (needs verification of dialogue features)
Ling & Chen, 2023	China	ASR-based translator for personalized learning	Pronunciation, vocabulary comprehension	Pronunciation ; vocab comprehension	Quantitative	S1 “ASR-enabled corrective pronunciation feedback” (needs verification); S2 “personalized vocabulary learning”
Rakhimova et al., 2024	Kazakhstan	AI tools for low-resource language dictionary	Vocabulary expansion	Vocabulary expansion & acquisition support	Quantitative	S6 “structured lexical resource for low-resource language learning”; NR “interactive/adaptive scaffolding not specified.”

Findings and Discussion

Findings are synthesized only from the included empirical studies (Table 2). Background literature is used solely for contextualization.

Ai Technologies and Learning Contexts in Early Childhood Language Development

Across the included studies, three main types of AI technologies were identified as supporting language learning in early childhood (≤6 years): conversational agents and chatbots, social robots, and speech-based AI tools such as automatic speech recognition (ASR) systems. Conversational agents and chatbots were most frequently applied in shared book reading and dialogic reading contexts, often involving parent-child or adult-child interaction (Leech et al., 2024; Cheng et al., 2024; Xu et al., 2021; Yuan et al., 2025). In contrast, social robots were primarily used in structured learning or experimental settings, where embodied interaction, gestures, and social presence played a central role (Jouen et al., 2025; Berrezueta-Guzman & Dolón-Poza, 2025; Yin et al., 2024).

Although studies were conducted across diverse national contexts, including China, Europe, and North America, reporting of learning settings (home, classroom, or laboratory) was often incomplete, limiting direct contextual comparison. Nevertheless, evidence suggests that AI-supported language learning in early childhood most commonly occurs in guided interactional environments, rather than in fully autonomous, child-only use contexts.

Target Language Skills and Reported Learning Outcomes

The reviewed studies predominantly focused on vocabulary development, followed by story comprehension, language participation, and oral expression. Vocabulary gains were most consistently reported in studies using social robots and conversational agents, particularly when interaction was repeated over time (Berrezueta-Guzman & Dolón-Poza, 2025; Cho & Yim, 2024; Jouen et al., 2025). Improvements in story comprehension and recall were mainly observed in dialogic reading contexts supported by AI agents, especially during shared reading activities (Xu et al., 2021; Vargas-Díaz et al., 2025).

While several quantitative studies reported statistically significant improvements in language outcomes, others did not find significant between-group differences despite noting increased engagement and interaction quality (Leech et al., 2024; Cho & Yim, 2024). This pattern suggests that interactional quality and participation may be more consistently enhanced than standardized language test outcomes, particularly in short-term interventions.

Patterns of Effectiveness Across AI-supported Learning Approaches

A recurring pattern across studies was that AI-supported learning tended to be most effective when embedded within interactive and socially mediated activities. Conversational agents used in shared reading contexts were associated with increased parent-child dialogue, child language output, and engagement, even when language gains were comparable to those achieved through adult-led instruction (Leech et al., 2024; Cheng et al., 2024; Xu et al., 2021).

Similarly, social robots demonstrated positive effects on vocabulary learning and motivation when they incorporated interactive behaviors such as eye contact, gestures, and turn-taking (Jouen et al., 2025; Yin et al., 2024). In contrast, AI tools used primarily for repetition or content delivery without interactive scaffolding showed more limited and inconsistent effects, highlighting the importance of interaction design rather than technology alone.

ZPD and Scaffolding Mechanisms Identified Across Studies

Analysis of the included studies using a sociocultural (ZPD) framework revealed several recurring scaffolding mechanisms. Dialogic elicitation (S4) was the most frequently identified mechanism, particularly in conversational agent and chatbot studies, where AI systems prompted children's responses, sustained dialogue, and encouraged narrative construction (Xu et al., 2021; Xiao et al., 2025; Yuan et al., 2025).

Social cues and joint attention (S3) emerged predominantly in robot-mediated interventions, with evidence showing that embodied behaviors such as gaze, gestures, and responsive movements supported vocabulary learning and engagement, especially in second language contexts (Jouen et al., 2025; Yin et al., 2024).

Adult mediation and co-scaffolding (S5) were central in shared reading studies, where AI functioned as a support tool rather than a replacement for adult interaction. These studies consistently reported enhanced engagement and recall when AI-supported reading was embedded within parent-child interaction (Leech et al., 2024; Vargas-Díaz et al., 2025).

Evidence for adaptive support aligned with children's ZPD (S2) was less frequently reported but was clearly observed in studies comparing controlled versus self-directed support modes. Findings indicate that children with weaker language skills benefited more from structured, guided AI support, whereas children with stronger skills performed better with more autonomous interaction (Yuan et al., 2025; van den Berghe et al., 2021).

Differences and Moderating Factors Influencing AI-supported Language Learning

Several moderating factors were identified across studies. Individual differences among children, including baseline vocabulary, speech memory, and attention, influenced the effectiveness of AI-supported interventions, suggesting that uniform AI applications may not benefit all learners equally (van den Berghe et al., 2021).

Teacher and adult involvement also played a critical moderating role. Studies consistently emphasized that AI technologies were most effective when accompanied by teacher guidance, emotional support, and instructional alignment, rather than being used in isolation (Cho & Yim, 2024; Yin et al., 2024; Jang et al., 2025).

In addition, contextual and cultural factors were noted as potential constraints. Some studies highlighted challenges related to speech recognition accuracy across accents and age groups, as well as limitations in cultural responsiveness of AI-generated content, which may affect learning outcomes in diverse settings (Li & Yu, 2025).

Summary of Key Findings

Overall, the findings indicate that AI technologies—including conversational agents, social robots, and speech-based systems—have considerable potential to support early childhood language development, particularly in vocabulary learning, story comprehension, and language engagement. However, their effectiveness is highly contingent on interaction quality, adult mediation, and alignment with children's developmental needs. When interpreted through a ZPD perspective, AI functions most effectively as a scaffolding tool within socially mediated learning environments, rather than as a standalone instructional substitute.

Future Research Directions

This systematic review contributes to the literature by synthesizing empirical evidence on AI-supported early childhood language learning through a ZPD-informed analytical framework. By identifying specific scaffolding mechanisms across AI applications, this review moves beyond outcome-based summaries to offer a mechanism-oriented understanding of how and why AI may support language development in early childhood.

Future research should more explicitly operationalize sociocultural constructs, report interactional details, and examine long-term developmental outcomes across diverse cultural and educational contexts. Such efforts are necessary to fully understand the role of AI as a mediational tool within children's evolving zones of proximal development.

Discussion

RQ1.How have AI technologies been applied to support early childhood language development, and what language learning outcomes have been reported across empirical studies?

Across the included empirical studies, AI has primarily been applied in early childhood language learning through three technological pathways: conversational agents/chatbots embedded in dialogic or shared reading activities, socially interactive robots that provide embodied engagement (e.g., gaze, gestures, turn-taking), and speech-based AI tools (e.g., ASR-supported learning/translation) targeting pronunciation and vocabulary practice (Xu et al., 2021; Cheng et al., 2024; Leech et al., 2024;

Jouen et al., 2025; Ling & Chen, 2023). Reported outcomes cluster around vocabulary acquisition, story comprehension/recall, and language participation (including increased child responses and parent–child dialogue), while effects on standardized language measures are more variable and sometimes non-significant despite observed gains in interactional engagement (Cho & Yim, 2024; Leech et al., 2024). Taken together, the evidence suggests that AI-based tools are most commonly positioned as interaction-support systems within learning activities rather than as independent tutors, and that outcomes are most consistently reported for proximal skills (e.g., vocabulary, comprehension) and participation-related indicators, whereas broader developmental impacts remain less consistently measured and are limited by heterogeneity in intervention duration, setting reporting, and outcome operationalization (Yuan et al., 2025; van den Berghe et al., 2021).

RQ2 What strengths and limitations of AI-supported language learning in early childhood emerge from existing research when interpreted through a sociocultural (ZPD) perspective?

When interpreted through a sociocultural (ZPD) lens, the central strength of AI-supported language learning lies in its potential to function as a mediational tool that structures children's participation in language-rich interaction—particularly through dialogic elicitation (prompts that elicit child talk), joint attention and social cues (embodied signals that sustain engagement), and adult co-scaffolding in shared reading contexts (Xu et al., 2021; Vargas-Díaz et al., 2025; Jouen et al., 2025). These mechanisms align with ZPD principles: learning is most likely when support is contingent, socially meaningful, and calibrated to the child's developing competence. Evidence also indicates that learner heterogeneity matters in ways consistent with ZPD expectations: children with weaker baseline skills may benefit more from structured or controlled AI support, whereas stronger learners may perform better with more autonomous interaction, implying that pedagogically grounded adaptivity—not merely algorithmic personalization—is a key design requirement (Yuan et al., 2025; van den Berghe et al., 2021). However, limitations emerge where AI fails to approximate core sociocultural conditions for early language learning. These include reduced capacity for emotionally responsive and culturally attuned interaction, technical constraints such as speech recognition challenges for young children and accent variation, and implementation risks if AI use displaces rather than complements adult mediation (Li & Yu, 2025; Cho & Yim, 2024). From a ZPD perspective, these constraints matter because breakdowns in contingency, cultural relevance, or adult regulation can shift activities outside the child's ZPD (over-scaffolding or under-supporting), thereby weakening learning opportunities and potentially exacerbating inequities.

Conclusion and Limitations

This review synthesizes recent empirical evidence indicating that AI-supported tools—most notably conversational agents/chatbots, social robots, and speech-based systems—can support early childhood language learning, with reported benefits most frequently observed in vocabulary growth, story comprehension, and language participation (Berrezueta-Guzman et al., 2025; Xu et al., 2021). When viewed through a sociocultural lens, these gains appear to be associated less with technology per se and more with the extent to which AI systems enable interactional scaffolding (e.g., dialogic prompting, joint attention cues) and are embedded within adult-mediated learning contexts.

However, the evidence base remains constrained by heterogeneity in study designs, contexts, and outcome measures, which limits generalizability across settings. Importantly, AI should not be framed as a substitute for human interaction: adult guidance and instructional alignment are recurrent conditions for effective implementation. Technical and contextual limitations also persist, including challenges in speech recognition accuracy for young children and diverse accents, which may disrupt contingent interaction and reduce learning benefits (Cho & Yim, 2024).

Future research should prioritize (a) longitudinal designs to examine sustained developmental effects and potential unintended consequences, (b) cross-cultural and multilingual evaluations to assess cultural responsiveness and transferability, and (c) clearer reporting and operationalization of scaffolding mechanisms (e.g., prompt contingency, fading, caregiver/teacher mediation) to enable cumulative, theory-driven evidence building. Overall, AI holds promise for supporting early language learning, but its educational value depends on developmentally appropriate design and implementation that complements, rather than replaces, socially mediated instruction.

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