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The Interaction of AI and Early Childhood Education. A State-of-the-art Review 2020–2024

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Abstract
This study offers a comprehensive state-of-the-art review of Artificial Intelligence (AI) and Early Childhood Education (ECE) research, focusing on publications from 2020 to 2024. The primary objectives are to map, analyse and answer research questions about the landscape of AI and ECE. The review process involved searching databases, including Scopus, ERIC, SpringerLink, ScienceDirect, and Web of Science. 39 studies were selected after applying exclusion criteria to ensure relevance to AI and ECE. This review adopts an international perspective, incorporating studies written in English, aiming to provide a global view of trends and practice of AI and ECE. Furthermore, the review categorises AI into classifications such as Traditional AI and Generative AI to identify trends within this field. The content analysis covers publication frequency, participant demographics, methodological approaches, and AI classifications while highlighting existing gaps in the current research on AI and ECE. The findings reveal a significant increase in AI research within ECE from 2020 to 2024, with a notable rise in publications in 2024. The results show that studies predominantly focus on children aged 4–6 and employ mixed-method approaches. Despite advancements, gaps in long-term studies, diverse population inclusion, and comprehensive ethical frameworks remain, underscoring the need for future research to address these issues.

Keywords Early childhood education · Artificial intelligence · AI · Digitalisation · Educational technology · Preschool

Introduction

The rapid advancements in Artificial Intelligence (AI) have prompted a surge in research to understand its potential and implications across various domains. One significant area of interest is education, where AI's transformative capabilities are explored to enhance learning experiences and outcomes. This, however, doesn't come without challenges and a need for critical reflection. Research has focused on how AI can be integrated into educational settings to support teachers and students, provide personalised learning, automate administrative tasks, and offer new ways to engage with educational content (Micheni et al., 2024). It is widely agreed that AI will increasingly influence education, including Early Childhood Education (ECE), but it is unclear how and to what extent (Su et al., 2023).

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AI's influence on ECE faces challenges and opportunities. It can potentially affect traditional teaching methods, making learning more interactive and tailored to individual needs. It is, however, imperative to reflect on the effects AI might have on younger children's development, for example, in areas such as language acquisition, problem-solving abilities, and social skills (Yang et al., 2024). Research indicates that while AI can enhance personalised learning, it cannot fully replicate the deeper interactions and relationship-building that are essential for comprehensive cognitive and social development (Panjeti-Madan & Ranganathan, 2023). Research in AI and ECE has identified significant gaps, including insufficient curriculum design, pedagogical development, teacher training, and a lack of AI knowledge among educators (Sanusi et al., 2022; Su et al., 2023; Su & Yang, 2023a; Yim & Su, 2024). Research also brings up data protection as a relevant concern within this field (Crescenzi-Lanna, 2023).

This state-of-the-art review aims to explore the field of research on AI and ECE between 2020 and 2024. This five-year timeframe is marked by unprecedented technological growth, with significant advances in AI, such as

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Generative-AI (GenAI), going mainstream in 2022 through various applications and technology designed for text generation, image creation, coding assistance, and other functionalities (Dwivedi et al., 2021; Mello et al., 2023; Roshanaei et al., 2023; Singh et al., 2025). The applications in education, particularly ECE, began expanding with the growing interest in AI. Given AI's potential to transform preschool education by altering teaching methods and influencing learning experiences and educational outcomes, it is crucial to investigate this emerging field. Prior research has focused primarily on AI literacy and pedagogical strategies in ECE rather than on the methodologies and AI classifications used in the research (Sanusi et al., 2022; Crescenzi-Lanna, 2023; Su et al., 2023; Su & Yang, 2023a; Yim & Su, 2024). This review addresses these gaps and provides valuable insights for future research and practice.

Aim and Research Questions

This state-of-the-art review aims to explore the field of research on AI and ECE between 2020 and 2024. The primary objectives of this review are (1) to map the existing research on AI in ECE settings, (2) to identify and analyse the theories, methodologies, and research questions prevalent in the field, and (3) to summarise these findings. This review adopts an international perspective, incorporating research from various regions where English-language studies are available. By doing so, it seeks to offer a comprehensive view of global trends and practices in AI's interaction with ECE.

The following research questions guided the review:

RQ1: What are the main research findings in artificial intelligence in early childhood education during 2020–2024?

RQ2: What gaps exist in the current research on artificial intelligence and early childhood education?

RQ3: Which artificial intelligence methodology is used in artificial intelligence and early childhood education research?

Background

This section provides background information with key concepts and a look into AI in education (AIED).

The integration of AI in education has a rich historical context, tracing back to the early days of computer-assisted instruction in the 1960s (Mello et al., 2023). Since COVID-19, AI technologies have evolved significantly, leading to more applications in educational settings (Dwivedi et al., 2021; Roshanaei et al., 2023; Singh et al., 2025). The development of AI has been marked by several key milestones, including the advent of machine learning, natural language processing, and, more recently, generative AI technology. These advancements have opened new possibilities for enhancing educational experiences. AI in Education (AIED) is a multifaceted field that leverages AI technologies to enhance educational experiences. According to Hamal et al. (2022), AIED has been the subject of academic research for over 30 years, examining learning in various settings, including traditional classrooms and workplaces, to support formal education and lifelong learning. It combines interdisciplinary AI and learning sciences, such as anthropology, education, linguistics, neuroscience, psychology, and sociology to develop adaptive educational settings and flexible, inclusive technology. AIED focuses on theories of human learning, AI applications in effective educational settings, and theories of teaching and AI applications in educational systems. It aims to define explicit forms of knowledge about education, including psychological and social aspects and explores the "black box of learning" (Hamal et al., 2022) to understand how learning occurs, the influence of socio-economic factors, physical context, and technology.

Researchers in AIED pay attention to emotional, social, and intellectual aspects of learning, with active research in collaboration, metacognition, self-regulation, motivation, and emotions. On the other hand, Lameras & Arnab (2022) defines AIED as the use of AI technologies to enhance educational experiences, focusing on practical applications such as personalised learning, intelligent tutoring systems, and data-driven decision-making. AIED aims to improve the effectiveness and efficiency of teaching and learning processes by integrating intelligent systems that adapt to individual learners' needs. While both sources agree on the fundamental role of AIED in enhancing educational experiences through AI technologies, Hamal et al. (2022) emphasise the interdisciplinary nature and theoretical aspects of AIED, whereas Lameras & Arnab (2022) focuses more on the practical integration and benefits of AI in educational settings. Together, these perspectives highlight the comprehensive nature of AIED and its potential to transform education.

A subfield to AIED is AIECE, combining AI and ECE (Fikri & Rhalma, 2024). This field focuses on integrating AI to improve the learning process and help foster creativity, literacy, and computational thinking skills in young children. This field also addresses aspects such as teacher training, curriculum development, and ethical considerations related to data privacy (Fikri & Rhalma, 2024). Despite the growing presence of AI technology like voice assistants, networked smart toys, and household robots in children's lives, there is limited research on using AI in early childhood (ages 1 to 8). AIECE examines computational thinking and creation, perception, learning, actions, senses, and sense-making processes. Younger children benefit most from hands-on learning, as they learn actively and intellectually. According to research conducted, there is potential for children to begin basic education regarding AI as early as three years old (Su, 2024c; Yang et al., 2024). However, more research in this field is needed.

Key concepts in AIECE include AI literacy, which refers to the understanding and ability to use AI technologies effectively (Luckin & Holmes, 2016). AI literacy involves the capacity to comprehend, utilise, oversee, and critically assess AI applications without developing AI models. It includes skills that enable individuals to evaluate AI technologies critically, interact and work effectively with AI, and apply AI as a technology in various settings (Laupichler et al., 2022). Another key concept in this field is machine learning. Machine learning is a field of AI that involves the development of algorithms and statistical models that enable computers to learn from data and make predictions or decisions without being explicitly programmed (Zhou, 2018). Machine learning has different approaches; text classification remains the most popular technique (Sokolova, 2018). Additionally, Generative AI (GenAI) is a subset of AI that uses deep-learning models to create new content such as text, images, videos, or other forms of data (European Commission, 2024). These models learn patterns and structures from existing data and use this knowledge to generate original content based on user prompts. The above-mentioned concepts are foundational to understanding AIECE.

Positioning the Current Review Within the Field of AIED and ECE

The relevance of this review lies in its ability to address a rapidly evolving interaction: AI and ECE. While previous systematic and scoping reviews have contributed valuable insights into AI in education, they often span broader educational contexts or focus on specific geographic regions or AI subfields. This review distinguishes itself by offering a focused and up-to-date analysis of AI research specifically within ECE from 2020 to 2024, a period marked by significant technological advancement and pedagogical experimentation.

Earlier reviews have laid important groundwork. For instance, (Sanusi et al., 2022) examined machine learning in K–12 education, identifying gaps in curriculum, pedagogy, and teacher training. Although not limited to ECE, their findings underscore the foundational challenges that also affect younger learners. Crescenzi-Lanna (2023) explored human-machine cooperation in ECE, emphasising digital ethics and the need for transparency and training; issues that remain central to AI integration in early learning environments. Su et al. (2023) conducted a thematic review of AI literacy in ECE, highlighting curriculum design, pedagogical approaches, and teacher preparedness as critical areas. Similarly, Su and Yang (2023a) reviewed computational thinking in ECE, identifying persistent challenges such as insufficient teacher knowledge and a lack of instructional guidelines. These studies collectively point to a need for more targeted research that supports educators in navigating AI's role in early learning. Yim and Su (2024) extended the scope to K–12 settings, identifying constructivist and play-based strategies as common in AI literacy education. While informative, their review spans a broader age range and does not isolate the unique developmental and pedagogical considerations of ECE.

In contrast, the current review focuses exclusively on AI research that includes the relevant age group in ECE, offering a more nuanced understanding of how AI is being integrated into early learning. By not limiting the scope to specific AI disciplines such as machine learning or generative AI, this review captures a wider spectrum of applications and pedagogical strategies. This comprehensive approach allows for the identification of emerging trends, persistent challenges, and knowledge gaps that are specific to ECE.

Ultimately, this review contributes to the field by providing educators, researchers, and policymakers with a clearer picture of how AI is shaping early childhood education. It supports informed decision-making and encourages thoughtful integration of AI technologies that align with the developmental needs and rights of young children.

AI Classification

It is important to examine relevant studies on classification to answer research questions concerning the use of AI methodology in studies.

Rani et al. (2023) compared various generative AI models and their applications. They highlight the differences between traditional AI and generative AI regarding purpose, learning approach, model architecture, applications, data requirements, and challenges. Traditional AI focuses on data analysis, forecasting, and classification using algorithms like decision trees and Support Vector Machines (SVMs). Traditional AI plays a crucial role in automating tasks (Su et al., 2024), with a history of application in healthcare, finance, retail, and manufacturing.

In the study by Bogner et al. (2019), traditional AI is defined as encompassing various approaches such as Machine Learning (ML), Artificial Neural Networks (ANN), and Deep Learning (DL). These approaches primarily focus on analysing and interpreting existing data to make predictions, classifications, or decisions. Bogner et al. (2019) also classify traditional AI as being used to label examples, identify patterns, and make predictions on new, unseen data. It is inferred that the primary goal of these models is to optimise performance metrics such as accuracy, precision, and recall.

Bogner et al. (2019) write that generative AI is built on the foundational concepts of traditional AI but focuses on generating new data. Instead of analysing existing data, generative AI models are designed to create new, synthetic data that resembles the training data. Generative AI models include Generative Adversarial Networks (GANs), Large Language Models (LLM), and Variational Autoencoders (VAEs), which can generate images, text, or audio. These models often use unsupervised or semi-supervised learning strategies, learning from the structure and patterns of the data rather than relying on labelled data. The goal of generative AI is inferred to be applied in many fields, such as medicine, linguistics and creative fields - such as art, music, and content creation - due to the possibility of creating, innovating, and complementing the analytical capabilities of traditional AI.

Bogner et al. (2019) emphasised traditional and generative AI's foundational concepts and theoretical differences. Rani et al. (2023) discussed a wider range of generative AI models and their application in various domains, such as education and entertainment. Both studies provide valuable insights into the differences between traditional AI and generative AI. However, Rani et al. (2023) offer a more detailed and application-focused analysis, while Bogner et al. (2019) provide a broader theoretical overview and methodological guidance.

Methodological Approach

This section describes the methodological approach for this study.

The aim and research questions are written based on the PCC framework (Population, Concept, and Context) (LibGuides, 2024). Other studies using the PCC framework include Archibald et al. (2016), Parker et al. (2021), and Peters et al. (2022). In this state-of-the-art review, the population consists of all roles that influence or are affected by using AI in ECE (for example, principals, teachers, children, students, and parents). The concept is AI, and the context is ECE. As such, it is important to note that this study employs a qualitative epistemological approach to explore the multifaceted nature of ECE (Patiño & Goulart, 2016). This impacts the method of the search strategy. This perspective acknowledges the complexity and subjectivity inherent in the field, recognising that knowledge is constructed through the interactions and experiences of various participants, including children, education, experts and parents. By adopting this holistic view, the study aims to provide a comprehensive understanding of ECE, where the focus is not solely on the children in a preschool setting but on the broader context involving all stakeholders, which emphasises the importance of considering subjective processes and their complexity in knowledge production (Patiño & Goulart, 2016). In practice, this means that the search for relevant studies is impacted and uses a larger scope than just narrowing down studies with children as participants.

Instead of doing a systematic review – that focuses on research questions that are narrow in scope – this study is a state-of-the-art review, defined with the aim of mapping the present state of knowledge about a phenomenon, the available data, the nature of the data, and gaps in knowledge (Barry et al., 2022b; Cevikbas et al., 2024).

This study follows six steps provided by (Barry et al., 2022a). The first step is to define the research question and the field of knowledge or practice to be targeted. The second step is to determine the time frame. The third step is to revise and finalise the research questions based on steps one and two. The fourth step is to create a search strategy. The fifth step is to analyse the included studies to construct an interpretation of the historical development and current understanding of the phenomenon. The sixth and final step is to provide a reflexive description for the review to ensure thoroughness and strength of interpretations, often in sections such as analysis or discussion. Steps one to three were written in the sections written previously; step four is shown in the section below. Steps five to six are shown in the result, discussion and conclusion parts of the article.

Identifying Relevant Studies

The electronic databases selected for this review were chosen due to their relevance, comprehensive topic coverage, and frequent use in similar reviews. ERIC (Education Resources Information Center) is widely used for early childhood education research, ScienceDirect is a central full-text database covering scientific research in health, life sciences, and physical sciences. Scopus provides broad multidisciplinary coverage, including technology and education fields. Springer Link offers access to scholarly articles and books, primarily in science, technology, and medicine. Lastly, Web of Science is a citation database that provides comprehensive coverage across multiple disciplines, emphasising high-impact journals and citation tracking. The identification of search results included using search strings and refined searching — Table 1.

While conducting the state-of-the-art review, different search strings were utilised for various databases to optimise the retrieval of relevant studies. This approach was

Table 1 Search strings and refined searching

Database	Search String	Datelast consulted
ERIC	nursery OR preschool OR kindergarten OR early childhood education AND artificial intelligence OR AI	2025-01-31
ScienceDirect	(nursery OR preschool OR kindergarten OR "early childhood education") AND ("artificial intelligence" OR "AI")	2025-01-31
Scopus	early childhood education AND artificial intelligence	2025-01-31
SpringerLink	(nursery OR preschool OR kindergarten OR "early childhood education") AND ("artificial intelligence" OR "AI")	2025-01-31
Web of Science	early childhood education AND artificial intelligence	2025-01-31
Refined Searching (Filters/Limits)	Year 2020–2024. Written Language: English Publications: Articles, Research papers. Keywords: Early Childhood Education and Artificial Intelligence. Subject: Artificial Intelligence, Social Science/Studies, Educational Science/Studies.	

experimental because each database has unique indexing systems, search algorithms, and keyword sensitivities. Consequently, some search strings yielded higher results in specific databases, while others did not correlate or work as effectively. Although this strategy may have resulted in a more significant initial pool of results and subsequently increased the workload during the exclusion process, it was the most thorough approach to ensure the inclusion of all pertinent studies.

Inclusion and Exclusion Process

The inclusion and exclusion criteria for this review were specified to ensure the relevance and quality of the selected studies. Studies were included if they focused on AI and Early Childhood Education (ECE) and met the criteria outlined in Table 2.

Exclusion criteria were applied to remove duplicates and any publications unrelated to AI and ECE. Additionally, publications lacking empirical data, such as opinion pieces, were excluded. Systematic, scoping, and state-of-the-art reviews were also excluded to avoid duplication, as these reviews are intended to map the available scope of a topic. The aim was to gather information directly from primary sources, ensuring a comprehensive and thorough review.

When looking for indicators for whether the publication was to be included or excluded, the abstract, the keywords, and the title were first read and reviewed. If needed, the whole article was read, and words in the studies, such as AI, preschool, kindergarten, and ECE (including abbreviations), were searched for to read sentences that might indicate a connection to the research subject. Studies referencing AI only for contextual relevance, without methodological engagement, were excluded to maintain focus on research where AI was central to design or analysis. To ensure consistency, the inclusion criteria prioritised studies where AI was central to the research design—either as a subject of investigation or as a methodological approach used to explore educational phenomena. This distinction is crucial: studies that merely referenced AI to contextualise their relevance, without integrating it into the research process, were excluded. In contrast, studies that employed AI as a methodological lens or as a means to study AI-related practices in early childhood education were considered highly relevant and included. Figure 1 shows the entire process, from identification, screening and exclusion to inclusion. This process excluded many studies, which may indicate that the search strategy could be further refined, or that the topic remains underrepresented in current literature.

The backward snowballing method was used to find studies that had not been included or excluded (Tsafnat et al., 2014). This entails reviewing the references of selected articles to find additional studies, which were done manually while reading each article. This method allows researchers to explore citations that may not have been captured through initial database searches. One study (Sung et al., 2023) was

Table 2 Inclusion and exclusion criteria

Inclusion Criteria	- Publications related to AI and ECE - Empirical data included - Focus on children aged 1–8 years, per definition of ECE - Keywords like AI, preschool, kindergarten, ECE
Exclusion Criteria	- Duplicates - Publications unrelated to AI and ECE - Opinion pieces - Digital technologies without AI - Broader age group/unclear age group - Reviews (literature, systematic, scoping, etcetera) - Non-English publications

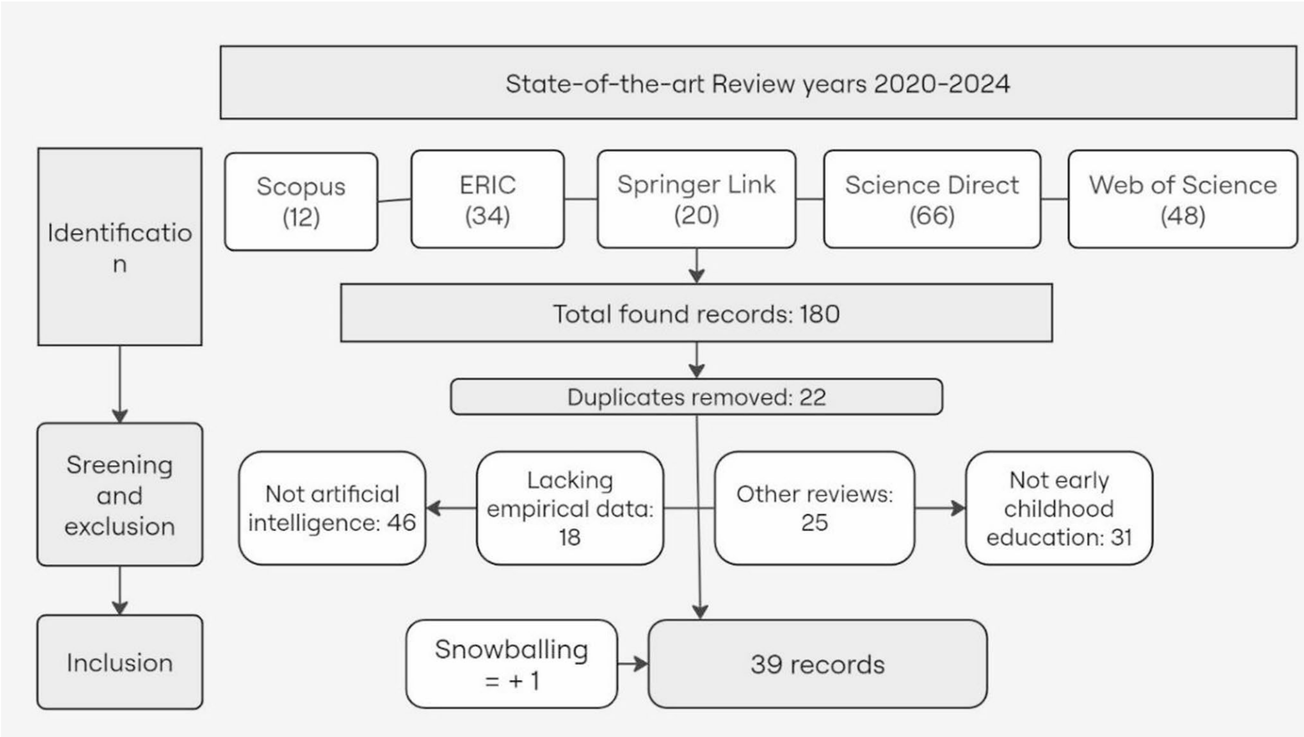

Fig. 1 Identification of articles in the state-of-the-art review

found in another article's "relevant studies" section. This study was included because it met all the inclusion criteria.

To ensure the rigour and relevance of the state-of-the-art review, it is essential to delve deeper into the specific exclusion criteria applied to the fields of AI and ECE. These criteria were pivotal in shaping the scope and focus of the review, ensuring that only the most pertinent studies were included. The following two sections provide a detailed examination of these critical exclusion criteria.

Exclusion Criteria: AI

In the field of study related to AI, various methods, including machine learning, serve as inclusion criteria because it is uncommon to find discussions of machine learning that do not reference AI explicitly. This was always checked before classifying whether the study was included or not. This decision and scope of inquiry were because machine learning is an integral part of AI and directly contributes to the development and functioning of AI systems.

Publications that only referred to 'digital technologies' or tools, such as tablets, without engaging with the concept of AI or mentioning AI were excluded from the review. This decision was made to maintain a clear focus on the integration and implications of AI within educational practices. Digital technologies like tablets do not inherently involve AI-based processes, which are central to the scope of this review. Consequently, studies that merely discuss the use of digital tools/technology without addressing AI were deemed outside the scope of the study. This makes the inclusion and scope of the search for AI in the exclusion process clearly defined, as studies discussing digital technologies without engaging in the AI process may lack the methodological rigor or conceptual focus on AI that this review requires.

A general inclusion criterion was the mention of AI in the abstract; however, instances arose where AI was cited merely as a justification for the research rather than being directly connected to the methodology or theoretical framework, leading to its exclusion from specific analyses. Consequently, while AI may serve as an underlying rationale for research, it does not necessarily constitute the primary theme or subject of the study. One example was a study about outdoor teaching in kindergarten, which mentioned how technology and AI might influence teaching in the abstract. In that specific publication, they only mentioned AI in one sentence to place the study in a general setting. In another example, some publications had abbreviations such as AI, even when they were not about artificial intelligence. Instead, they were connected to other terms and theories with the same abbreviation. Another publication was written in a journal that had Artificial intelligence in its name. The publication never mentioned "artificial intelligence" or the abbreviation AI. However, the content, such as methodology and theory, was directly connected to the topic and was included in the review due to all other inclusion criteria.

Exclusion Criteria: Early Childhood Education

The inclusion criteria for this study are the definition of ECE, which relates to teaching children one to eight years old. Countries might use other names and settings relating to age groups, such as kindergarten, nursery, and preschool, that are included in the parameter of ECE as mentioned above. For example, in Sweden, preschool is the setting for children aged 1 to 6 years old, and in the United States, the usual age for children in Preschool is 3 to 5 years old. ECE encompasses all these definitions and settings related to the age group. The scope involved teachers, students/children, parents, and other roles connected to ECE.

While screening the publications, some were not about education or ECE. The search strings in Table 1 sometimes allowed these to pass through despite refined searching. Due to this, Exclusions were made, as previously shown in Fig.1.

A few publications mentioned “schools” in their data collection but did not mention the age group of participants or show any clear connection to ECE. This made it difficult to judge if the data was collected with the age group in mind for this review. Studies were deemed to lack empirical and well-defined data collection since it was unclear what kind of school the children attended – to a degree where it was difficult to tell if the children were in preschool or young adults in higher education. Therefore, studies had to be excluded from this review. Similarly, if publications referred to “children” as the primary data collection group, the age range’s ambiguity complicates interpretation. Many countries’ definition of a child encompasses individuals under 18 years old. Such discrepancies hinder the credibility of the publication and create a disconnect with the field of ECE, making it challenging to engage with the findings meaningfully. This also excluded studies from this review due to a lack of or insufficient empirical data.

Some publications focused on a broader age range, specifically K–12 education, which includes the target age group. This term is used more commonly in the United States and Canada to express the school system for children from kindergarten to school year 12. This group includes children ages 5 to 17. In other countries, such as Australia, a related term, P–12, refers to the sum of K-12 plus preschool education. This broader scope made analysing the findings in these publications more complex. These publications were often excluded from the review. Even if the age group is defined, it encompasses the entire school system and does not explicitly focus on ECE. One example of an excluded publication had interviewed teachers from K–12, but no participating teacher worked with children aged 1–8. Another excluded study encompassed a wide age range of children, making it impossible to validate as part of ECE.

Analysis Method

A summative content analysis of studies was conducted to answer this state-of-the-art review’s research questions. The research aims and results were analysed within the setting of each study to identify trends, gaps, and valuable information, such as publication trends, geographical distribution, and methodologies. Additionally, the review examined theoretical frameworks and conceptual models to understand their impact on findings. The implications of the findings for future research and practice were explored, highlighting areas for further research. As Hsieh and Shannon (2005) mentioned, a summative approach to qualitative content starts with identifying and quantifying certain words or content in a text to understand their contextual use. This quantification explores usage rather than inferring meaning, referred to as manifest content analysis. Summative content analysis goes beyond word counts to include latent content analysis and interprets the content to discover underlying meanings. In this review, the initial analysis involved quantitative aspects like publication trends and methodologies, followed by the interpretation of underlying meanings and implications, thus employing both manifest and latent content analysis characteristic of summative content analysis (Hsieh & Shannon, 2005).

Results

This section starts by presenting an overview of selected studies, with information such as publication trends within AI and ECE between 2020 and 2024 (see Fig. 2), age

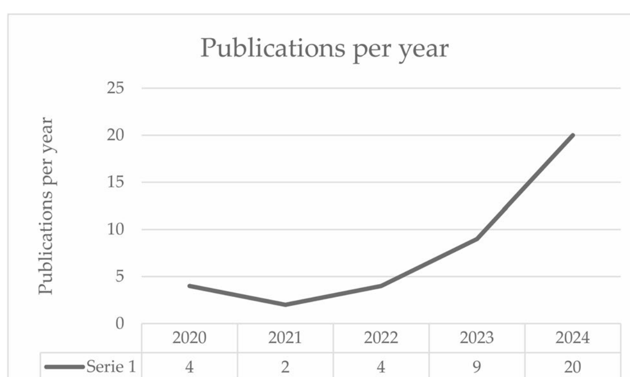

Fig. 2 AI in ECE 2020–2024: Publications Per Year

range, and participants in these studies. With this information brought to the reader, the next session answers each research question in order.

This state-of-the-art review included 39 publications. Twenty of these studies were published in 2024, showing a vast increase in publications within this field compared to previous years.

The analysis of the geographical distribution of published studies reveals that Asia, particularly China, is the most prominent region, with 13 studies highlighting its significant contribution to the research field. Studies from Europe, North America, and Australia show the global nature of research efforts, showcasing a wide range of geographical contexts and expertise. Additionally, contributions from regions like Africa and Cyprus suggest a growing interest and investment in this field of research.

The analysis of the study's age groups reveals a significant focus on specific ages, see Fig. 3. The median age across the studies is approximately 5 years, while the mean age is around 4.74 years. Additionally, the age with the highest density, indicating the most frequently mentioned and studied age, is 6 years (mentioned 18 times in the data). This suggests that most research concentrates on children within this age bracket. There is a noticeable clustering of studies focusing on ages 3 to 6. Conversely, there are fewer studies on very young children (under 2 years) and older children (above 7 years), highlighting potential gaps in research within these age groups.

The chart shows the distribution of participant groups in the included studies. It shows that most studies focus on children aged 4–6, followed by educators and teachers, and children with broad age ranges (1–8, 1–6, 3–9). Other participant groups include parents, children aged 1–3, children older than 6 years, AI and robotics experts, mixed participants, and university students. As a reminder, since the study uses a qualitative epistemological approach, these studies involve different participant groups, such as parents and teachers, while maintaining the specific age range definition of early childhood education (ECE) of 1–8 years is the main objective. For instance, studies involving parents were conducted because these parents had children in specific age ranges, such as 1–3 or 3–5 years, within the ECE age range. Similarly, studies involving university teachers were involved in ECE programmes at these universities. This ensures that all studies maintain a consistent focus on early childhood education.

Furthermore, the methods used in the studies vary, see Fig. 4.

The 39 studies were categorised as either mixed-method approach, Experimental Design, Qualitative Method, or Quantitative Method. This classification was based on the information provided in the methodology sections of each study and an interpretation of the methods used. Some studies used either quantitative or qualitative methods exclusively, some used a mixed-method approach incorporating both qualitative and quantitative methods, and some used

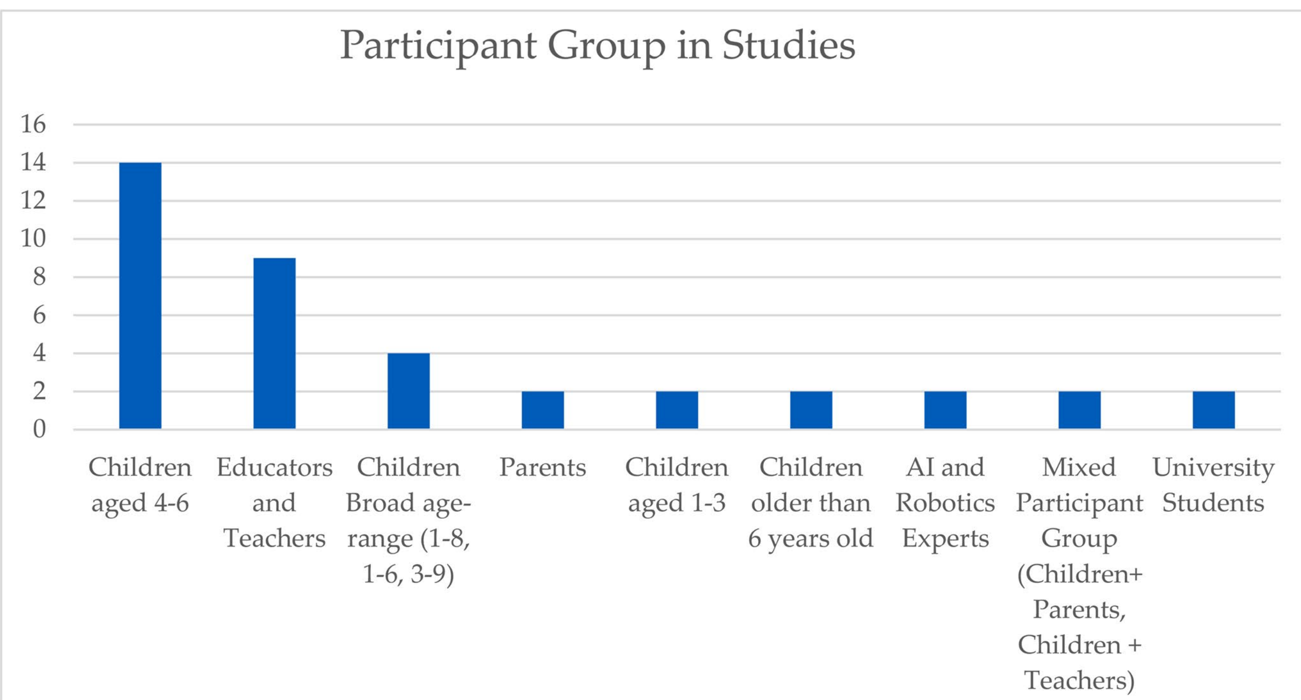

Fig. 3 Participant group in studies

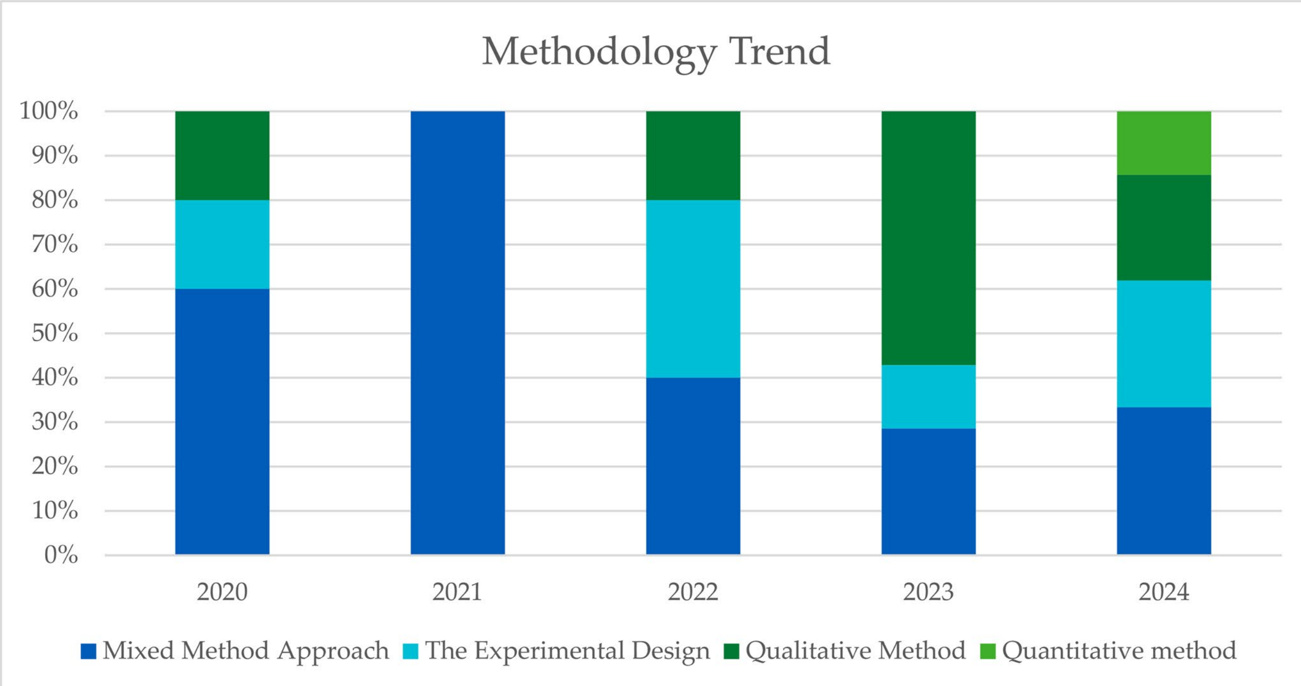

Fig. 4 Participant Group in Studies

experimental designs. The latter are characterised by their experimental nature, typically involving pre- and post-tests with a control group and an experimental group.

The most common methodology used in these studies is the Mixed-Method Approach, with 15 studies. Studies using the qualitative method were the second most common, with 11 studies, followed by experimental designs with 10 studies. Lastly, the quantitative method had 3 studies. During the years 2020–2024, the mixed-method approach was present every year, but it was also increasing, starting with 3 studies in 2020 and 9 studies in 2024. Quantitative studies were not used until 2024. The year 2021 was the year of mixed methods.

The Main Research Findings

The studies consistently highlight the transformative impact of AI on learning outcomes and engagement. Studies such as those by Abbas et al. (2021) and Ganesh et al. (2022) demonstrate that interactive AI technologies, like mobile apps designed for categorisation skills and AI Pop Bots for understanding AI concepts, led to higher engagement and comprehension among the participating children. These technologies provided an interactive and personalised educational experience, which was argued as crucial for maintaining children's interest and improving their learning outcomes. Additionally, Aslan et al. (2024) highlighted the effectiveness of immersive multi-modal systems like Kid Space in reducing concerns about screen time while promoting physical activity and social interactions. This study addressed the concerns about how screen time might impact children's development.

AI-integrated educational programmes were brought up in some studies and described as being instrumental in developing computational thinking and problem-solving skills in young children (Falloon, 2024). Research by Falloon (2024) indicates that structured, problem-based curricula and AI-integrated educational programmes enhance children's abilities in sequencing, error correction, and pattern recognition. The use of educational robots and coding activities, as found in various studies, has also been effective in improving computational thinking and executive function skills (Gümüs et al., 2023; Whitehill & LoCasale-Crouch, 2024; Zurnacı & Turan, 2024). Both digital and unplugged methods have demonstrated positive impacts, highlighting the versatility and effectiveness of AI technologies in fostering essential cognitive development.

The development of AI literacy and inquiry skills is another critical theme emerging from the research. AI-literacy frameworks like SIACC, developed by Luo et al. (2024a, b), emphasise the importance of AI safety awareness, digital identity, and ethical AI use. These frameworks aim to prepare children for an AI-driven future by promoting critical thinking and responsible AI use. Additionally, AI-interfaced toys and technologies, as those studied by Kewalramani et al. (2021), were shown to foster inquiry literacy by encouraging creative, emotional, and collaborative inquiry among children. According to Kewalramani et al. (2021), these technologies help children develop higher-order thinking skills and a deeper understanding of AI concepts.

However, the perceptions of teachers and parents towards AI in early childhood education are mixed, reflecting both optimism and concern. Studies by Kucirkova et al. and Mohammed (2023) reveal that while teachers and parents recognise the potential benefits of AI in enhancing educational experiences, they also express concerns about privacy, data security, and the practical challenges of implementation. The researchers in these studies bring up the need for ongoing professional development, ethical guidelines, and collaboration among stakeholders to ensure the responsible and effective integration of AI in early childhood educational settings.

Studies indicate that social interaction, whether with humans or AI technologies, significantly enhances children's conceptual development (Zuo et al., 2023). The study argues that children supported through social interaction, whether with humans or AI technologies, demonstrated significant improvements in conceptualisation, indicating the importance of incorporating social interaction into AI-based educational technologies.

AI technologies have been mentioned in relation to early detection and personalised learning, particularly in identifying children with diverse learning needs and tailoring educational experiences to individual needs. For instance, the AI pre-screening technology for Autism Spectrum Disorders (ASD) developed by Paolucci et al. (2023) achieved high accuracy in early detection, underscoring the potential of AI in personalised learning and early intervention.

In conclusion, while most studies mention the benefits of integrating AI in ECE, researchers also present several challenges, such as ethical concerns, data privacy, and the practical challenges of implementation. Most studies mention the need to provide comprehensive support and targeted training for educators and caregivers for the effective integration of AI in ECE. Additionally, a balanced approach that emphasises the importance of human agency and inquiry skills can be discerned as essential. The main conclusion drawn from the studies is that AI should be used to augment rather than replace human educators, ensuring that children receive a well-rounded and holistic educational experience.

The Knowledge Gaps in Existing Research

The research objectives in the current studies vary widely, from assessing the impact of digital technology on specific skills like handwriting and math to exploring broader themes such as personalisation, privacy, and the role of AI in fostering inquiry literacy. However, several significant gaps remain. One major gap is the absence of long-term studies that track AI technology's developmental and educational impacts on children over extended periods. Such studies could provide valuable insights into AI technologies' sustained effects and potential drawbacks, including their impact on children's social skills and ability to form relationships, particularly in collaborative educational settings. Another gap is the lack of research involving diverse populations. Current studies often overlook children's experiences from various cultural, linguistic, and socioeconomic backgrounds. More research is needed to understand how AI technologies affect these diverse groups and how cultural contexts influence their interactions with AI.

Ethical concerns are frequently mentioned in the studies. These tend to mention practical elements, such as data privacy and integrity of the children in the study, instead of the ethical use of AI and how it might impact children's development. There is also a lack of comprehensive frameworks guiding the responsible use of AI in early childhood education. Research could explore how to develop and implement such frameworks effectively, ensuring that AI technologies are used responsibly in research. More research needs to be focused on designing and evaluating AI technologies tailored explicitly for the ECE age group. This includes understanding young children's unique needs and developmental stages to create age-appropriate AI technologies.

The reviewed studies show a lack of participation by children between 1 and 3 years of age, parents, and AI experts. Including these groups in future research could provide a more comprehensive understanding of AI's impact on early childhood education. Additionally, there is a research gap in understanding children's specific cognitive processes when interacting with AI technologies. More in-depth research is needed to explore how these technologies influence critical thinking and problem-solving skills. Finally, interdisciplinary research is needed to combine computer science, education, ethics, and psychology insights to understand AI's role in early childhood education. This approach can help address the complex and multifaceted nature of AI's impact on young learners.

In conclusion, the common theme across these studies is the broad and general discussion of AI technologies, particularly in educational contexts. This broad approach, combined with a focus on AI's potential benefits and applications, leads to a lack of specificity and difficulty in categorising the mentioned AI methodologies. To improve clarity, future studies could benefit from more precise definitions and categorisations of AI types, particularly when discussing their applications and implications.

Table 3 Categorisation of artificial intelligence methodology

Traditional AI	Generative AI	Inconclusive/Unclear
(Abbas et al., 2021; Aslan et al., 2023, 2024; Bonneton-Botté et al., 2020; Del Moral-Perez et al., 2024; Ganesh et al., 2022; Gulz et al., 2020müs et al., 2023; Kewalramani et al., 2021; Kucirkova et al., 2021; Li, 2024; Lim, 2024; Paolucci et al., 2023; Pitta-Pantazi et al., 2024; Prasad et al., 2022; Samuelsson, 2023; Su, 2024c, 2024a; Su et al., 2024; Su & Yang, 2024; Xu et al., 2022; Yang et al., 2024; Yıldız, 2020; Zhang et al., 2024; Zurnacı & Turan, 2024)	(Luo et al., 2024b; Su & Yang, 2023b; Uğraş et al., 2024; Uğraş & Uğraş, 2024; Whitehill & LoCasale-Crouch, 2024)	(Axell & Berg, 2024; Falloon, 2024; Luo, He, Gao et al., 2024; Mohammed, 2023; Su, 2024b; Su and Yang, 2023a; Su & Zhong, 2022; Sung et al., 2023; Zuo et al., 2023)
25	**5**	**9**

The Classification of AI

The classification of AI is shown in Table 3.

Most studies are categorised as Traditional AI, with examples such as Su and Yang (2024), Li (2024), and Gümüs et al. (2023). The Generative AI category comprises five studies, making it the smallest category after the Inconclusive/Unclear category. The Inconclusive/Unclear category includes nine studies, with examples such as Mohammed (2023), Zuo et al. (2023) and Luo et al. (2024). Based on the AI classification by Bogner et al. (2019), mentioned in previous sections, the results show an increasing trend in the number of studies related to Traditional AI and Generative AI over the years, with a notable increase in 2024 (Fig. 5).

Traditional AI had the highest increase, from 4 published studies in 2023 to 12 published studies in 2024. Of 39 studies, 25 overall were classified as Traditional AI, making it the most common. This classification aligns with the definitions provided in previous sections by Bogner et al. (2019), where Traditional AI encompasses approaches like Machine Learning (ML), Artificial Neural Networks (ANN), and Deep Learning (DL), focusing on analysing and interpreting existing data. In contrast, Generative AI, which has also seen an increase, focuses on generating new data and includes models like Generative Adversarial Networks (GANs), Large Language Models (LLM), and Variational Autoencoders (VAEs). The increasing trend in both Traditional and Generative AI studies highlights the evolving landscape of AI research and its expanding applications. When a study seemed to contain both traditional AI and generative AI theories and methodologies, the results of the studies maintained the biggest impact of categorisation. For example, Whitehill and LoCasale-Crouch (2024) mentioned Large Language Models (LLM) and Bag Of Words (BoWs) as concepts, but due to the main focus of not just context and results on LLMs, it was placed under generative AI.

The studies that mention the concept of AI-literacy predominantly were placed under traditional AI for several reasons (Kewalramani et al., 2021; Yang et al., 2024). First, the context and explanation for what the studies refer to as AI-literacy encompasses foundational principles and early methods, crucial for understanding the evolution of AI. Second, by analysing the educational framework of these studies, the focus is on teaching basic concepts to build a solid

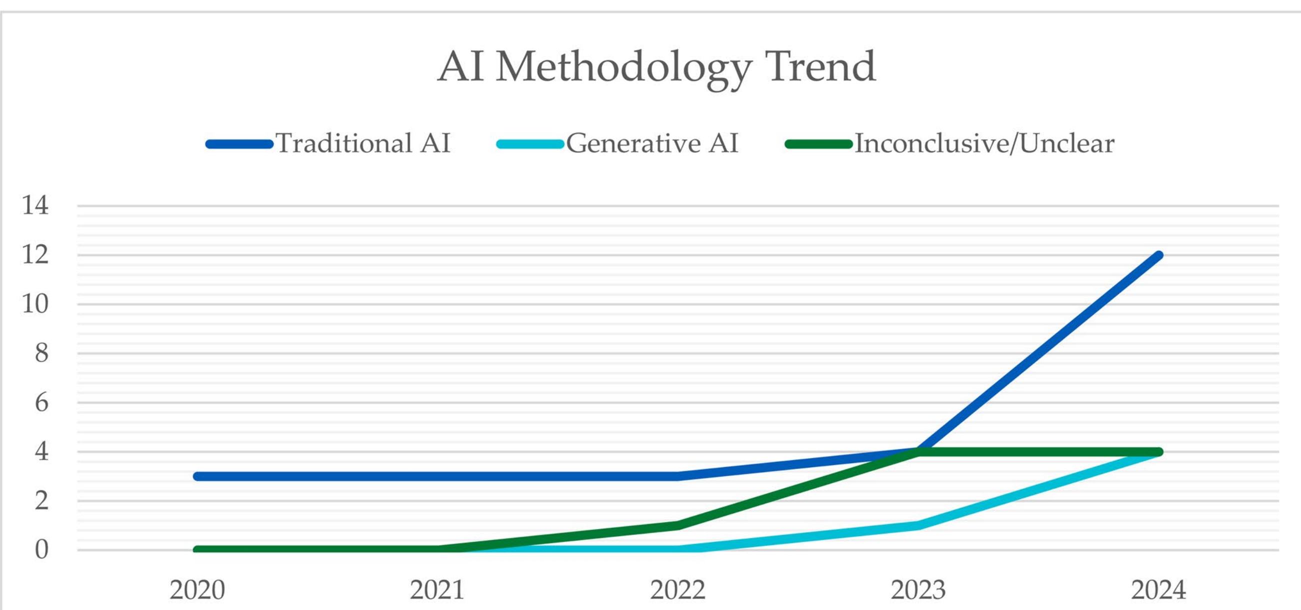

Fig. 5 AI in ECE 2020–2024: Publications Per Year

foundation of knowledge about AI. Additionally, when discussing the ethical and societal impacts of AI, which is integral to AI literacy, the studies often reference traditional AI methods. Lastly, some practical applications in these studies are referred to as traditional AI.

Besides this, several studies were classified as inconclusive/unclear, highlighting the challenge of categorising AI methodology when the definitions and applications are not specified. These studies share common themes, including their broad definitions of AI. They mention AI technologies in general terms without specifying whether they are discussing traditional AI, generative AI, or another specific type. This is done by mentioning the abbreviation of AI without a clear definition of the term. This broad approach also makes it difficult to categorise the AI technologies mentioned. The definitions of AI in these studies are often broad, describing AI as systems capable of making predictions, providing recommendations, or simulating human thinking and actions. This lack of specificity contributes to the difficulty in categorising AI methodology.

For example, Su (2024b) mentions AI-literacy, so it might have suited in the traditional AI category according to the previously mentioned reasons, but the study defines AI in general terms to introduce the reader to the use of AI in education. The definition provided—AI as a machine-based system capable of making predictions and providing recommendations— does not lend itself to a precise classification as traditional AI or generative AI, but instead, perhaps both. Similarly, Zuo et al. (2023) discuss AI in the context of robotics education for young children, defining AI as technologies that enable robots to simulate human thinking and actions. This broad definition makes it challenging to categorise the AI mentioned. Mohammed Asalaam (2023) discusses AI in early childhood education in Ghana, defining AI as technologies that enhance teaching and learning experiences, provide personalised instruction, and support early childhood development. Again, this broad definition does not specify the types or applications of AI. Axell and Berg (2024) focus on programmable artefacts and robots, which can include AI elements but do not explicitly define AI. Instead, they focus on children's conceptions of programming and programmable artefacts. Su and Zhong (2022) and Su and Yang (2023) both discuss AI in early childhood education, defining AI as technologies that enhance teaching and learning experiences and provide personalised instruction. These studies emphasise the importance of AI literacy but do not specify AI models, concepts or applications. Similarly, Luo et al. (2024a, b) discuss AI literacy in early childhood education, defining AI as a broad range of technologies that can think, learn, and interact like humans.

Discussion

The findings of this state-of-the-art review reveal several critical insights and areas for further exploration within AI and ECE. One notable observation is the significant focus on children aged 4–6, with fewer studies addressing very young children (under 2 years) and older children (above 7 years). This concentration on specific age groups raises essential questions about the developmental appropriateness and potential benefits or drawbacks of AI technologies for different age ranges. Research involving children aged 1–3 is particularly sparse, possibly due to ethical considerations, the challenges of engaging very young children in structured studies, or the perception that AI technologies are less suitable for this age group. Future studies would benefit from consider the unique developmental needs of this age group and explore how AI can be designed to support their growth safely and effectively. One result was also that AI-experts was less part of the studies, as participants, as well as teachers, parents and university students. This could be due to a view of children's participation as important in the field of ECE, making it more suitable to involve children themselves as participants. However, from a epistemological approach, the lack of perspectives makes it more difficult to untangle an already complex and subjective inherent in AI and ECE (Patiño & Goulart, 2016). If knowledge is constructed through interactions and experiences between individuals, the lack of inclusion of a broader group of participants diminishes the overall understanding of AI and ECE.

Several significant gaps were identified in the current studies. The absence of long-term studies is a critical gap that needs to be addressed to understand the sustained effects of AI on children's development. Additionally, the lack of research involving diverse populations points to a need for more inclusive studies that consider the experiences of children from various cultural, linguistic, and socioeconomic backgrounds.

The dominance of mixed method approaches in the reviewed studies reflects the complexity of researching AI in ECE. Mixed methods provide a comprehensive understanding by combining quantitative data with qualitative insights (Creswell & Creswell, 2023). However, the relatively low number of quantitative studies suggests a gap in rigorous, data-driven research. Quantitative studies are essential for providing statistically significant evidence of AI's impact, which can complement the rich, contextual data obtained from qualitative research. The increasing trend in experimental designs is a positive added development, as these studies can provide robust evidence of causality. Nonetheless, the field would benefit from more longitudinal studies that track the long-term effects of AI interventions.

The classification of AI methodologies (Bogner et al., 2019) shows a clear preference for traditional AI approaches, such as machine learning and neural networks. The emergence of generative AI indicates a shift towards more innovative applications. However, studies with inconclusive or unclear methodologies highlight the need for more precise definitions and categorisations. This ambiguity can hinder the synthesis of findings and the development of a coherent body of knowledge.

Ethical Considerations in AI and ECE

Ethical concerns, while frequently mentioned, lack comprehensive frameworks guiding the responsible use of AI in ECE. Developing and implementing such frameworks is essential to ensure that AI technologies are used ethically and responsibly. This issue has arisen from previous reviews, most notably the need to address both a lack of knowledge among teachers, a lack of curriculum design and the absence of clear teaching guidelines (Crescenzi-Lanna, 2023; Sanusi et al., 2022; Su et al., 2023; Su & Yang, 2023a, b). This review confirms that ethical concerns persist in the 2020–2024 period, echoing earlier findings. These concerns persist in the 2020 to 2024 period, indicating a continued gap in ethical guidance. Drawing on the scoping review by Berson et al. (2025), three interrelated domains emerge as central to understanding the ethical challenges in this field: data privacy, developmental impacts, and algorithmic bias.

Data privacy is particularly critical in ECE, where AI systems often collect sensitive behavioural, biometric, and emotional data from children who lack the cognitive maturity to understand or consent to such practices. Berson et al. (2025) highlight that many AI tools operate as opaque systems, with limited transparency regarding data collection, retention, and sharing. This raises concerns about surveillance, profiling, and long-term implications for children's digital identities. The review also notes that parental consent alone is insufficient, especially when children interact independently with AI-powered toys or classroom applications. Ethical AI design must therefore incorporate child-friendly privacy safeguards and mechanisms for meaningful assent. These concerns are reflected in the reviewed studies, where emotional data were rarely the focus of research, despite their relevance to children's development.

Developmental impacts are another key concern. AI systems must align with the unique developmental needs of young children, who learn through exploratory play, multimodal interaction, and relational experiences. Berson et al. (2025) argue that many existing AI tools prioritise efficiency and academic outcomes over relational and experiential learning. This disconnects risks undermining emotional development and reducing opportunities for co-constructed knowledge. Out of the 39 studies, only a handful brought up the emotional development of young children. In those cases, this was brought up as a point of critical discussion and not as part of the study's aim. Most studies focused on cognitive skills such as problem-solving, pattern recognition and critical thinking, which shows a knowledge gap in this field (Garner & Waajid, 2012; Panjeti-Madan & Ranganathan, 2023). However, some studies involving play-based learning with AI toys (Kausar et al., 2024) suggest potential for supporting social development, reinforcing the argument that emotional and social development are intertwined.

Algorithmic bias presents a third ethical dilemma. AI systems trained on non-representative datasets can perpetuate systemic inequities, disproportionately affecting marginalised communities. Berson et al. (2025) emphasise that biased outputs may influence teacher expectations, assessment outcomes, and children's self-perception. This is especially concerning in ECE, where early experiences shape identity and learning trajectories. Addressing bias requires culturally responsive design, diverse training data, and transparent decision-making processes. The lack of diverse populations in the reviewed studies further underscores the need for inclusive research that reflects the varied backgrounds of children in early learning environments.

These ethical dimensions are not peripheral but central to the responsible integration of AI in ECE. Future research should prioritise the development of child-centered ethical frameworks, involve educators and families in co-design processes, and ensure that AI tools support rather than hinder holistic child development. As Berson et al. (2025) conclude, safeguarding children's rights and well-being must be foundational to any AI innovation in early learning environments.

Conclusions

The review highlights several critical insights and areas for further exploration within AI and Early Childhood Education (ECE). There is a significant focus on children aged 4–6, with fewer studies addressing very young children (under 2 years) and older children (above 7 years). This raises questions about AI's developmental appropriateness and potential benefits or drawbacks for different age ranges. Research involving children aged 1–3 is particularly sparse, possibly due to ethical considerations, challenges in engaging very young children in structured studies, or perceptions that AI technologies are less suitable for this age group.

The dominance of mixed method approaches reflects the complexity of researching AI in ECE. Mixed methods provide a comprehensive understanding by combining quantitative data with qualitative insights. However, the relatively low number of quantitative studies suggests a gap in rigorous, data-driven research. Quantitative studies are essential for providing statistically significant evidence of AI's impact, complementing the rich, contextual data from qualitative research. The increasing trend in experimental designs is positive, as these studies can provide robust evidence of causality.

The classification of AI methodologies shows a preference for traditional AI approaches, such as machine learning and neural networks. The emergence of generative AI indicates a shift towards more innovative applications. However, studies with inconclusive or unclear methodologies highlight the need for more precise definitions and categorisations. This ambiguity can hinder the synthesis of findings and the development of a coherent body of knowledge.

Several significant gaps were identified in the current studies. The absence of long-term studies is a critical gap that needs to be addressed to understand the sustained effects of AI on children's development. Additionally, the lack of research involving diverse populations indicates a need for more inclusive studies considering children's experiences from various cultural, linguistic, and socioeconomic backgrounds. While frequently mentioned, ethical concerns lack comprehensive frameworks guiding the responsible use of AI in ECE. Developing and implementing such frameworks is essential to ensure that AI technologies are used ethically and responsibly.

Future Research

Future research could aim for greater specificity in defining and categorising AI methodologies to enhance clarity and comparability across studies. More precise definitions and categorisations of AI types could improve clarity, particularly when discussing their applications and implications. Additionally, the field of AIECE might benefit from more longitudinal studies tracking the long-term effects of AI interventions. Future studies could consider the unique developmental needs of very young children and explore how AI can be designed to support their growth safely and effectively. Furthermore, there is a need for more inclusive studies that consider the experiences of children from various cultural, linguistic, and socioeconomic backgrounds. Lastly, one of the most important future studies would entail developing comprehensive frameworks to guide the responsible use of AI in ECE. This is essential to ensure ethical and responsible implementation.

Limitation

While my expertise lies in ECE, I have strengthened my AI competence through formal coursework and advisory support from AI experts. These experts provided feedback on terminology and conceptual clarity without contributing to the writing or analysis process.

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