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A Scoping Study of AI Affordances in Early Childhood Education: Mapping the Global Landscape, Identifying Research Gaps, and Charting Future Research Directions

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Abstract

Artificial intelligence (AI), manifested in the forms of technologies, systems, tools, and applications, has advanced rapidly, especially in recent years. It has permeated many aspects of human behavior and nearly all sectors of society, such as healthcare and education. In the context of early childhood education (ECE), AI has afforded valuable opportunities that directly and indirectly enhance children's learning and development. While there are already two existing reviews of the literature on AI in ECE, they show either a lack of descriptive information concerning selected studies or inconsistencies between inclusion/exclusion criteria and selected studies, thereby raising concerns about their rigor. Representing a more methodologically rigorous effort and a significant contribution to the field of AI in ECE, this scoping study aimed to achieve three main goals: (1) "mapping" the global landscape of the current extent, range, and nature of relevant studies on the affordances of AI for use in ECE, (2) identifying potential research gaps, and (3) charting future research directions. Specifically, it addressed this overarching research question: *What is the global landscape of the current state of knowledge concerning the affordances of AI for use in ECE?* Specifically, the *state of knowledge* here refers to three aspects: (1) extent, (2) range, and (3) nature. First, regarding the extent aspect, the empirical knowledge was derived from 18 research articles in 11 countries and 16 peer-reviewed academic journals between 2005 and 2023, with 14 of these articles published in the past four years (2020–2023). Second, with respect to the range of study populations, it covered 15,081 children in early childhood (ages 2 to 8 years) across these 11 countries. Third, thematic analysis of these studies revealed four areas of AI affordances: (1) AI as tangible and intangible tools for interactive learning and information retrieval, (2) AI as technology for predicting/classifying children's conditions, (3) AI as the object for learning by adapting to and personalizing children's learning, and (4) AI as the subject for children's learning about it. Based on these findings, this scoping review identified three research gaps for future studies: (1) interviewing and/or surveying education stakeholders (parents, educators, policymakers) to explore the affordances of appropriate AI for use with, by, and for children bearing ethical considerations; (2) conducting group comparisons to investigate contextual factors contributing to the "AI divide" among children from different socioeconomic backgrounds; and (3) comparing sociocultural influences on AI use in ECE across cultures.

1. Introduction

Artificial intelligence (AI) is a term that was first coined by McCarthy et al. (1955) in their written proposal for a summer research conference on AI to occur in 1956 at Dartmouth College in the United States. AI is considered a subfield of computer science and encompasses advanced technologies that are essential for achieving human-like intelligence. These advanced technologies include AI techniques and applications, such as machine learning, deep learning, and learning analytics (Crescenzi-Lanna, 2023). Despite the increased prominence of AI in public discourse, particularly over the past decade, there has not been a singular, universally accepted definition of AI. Some of the earliest definitions of AI include those characterizing it as an artificial system (e.g., a computer or a machine) or a set of techniques designed to imitate and simulate the natural human intelligence required to perform intricate tasks and cognitive functions, such as solving complex problems and engaging in adaptive learning (Calo, 2017; Ludger, 2009; McCarthy, 2007).

More recent definitions approach AI from cognitive and social perspectives. For instance, Abbass (2021) defined AI as "the automation of cognition" as well as "social and cognitive phenomena that enable a machine to socially integrate with a society to perform competitive tasks requiring cognitive processes and communicate with other entities in society by exchanging messages with high information content and shorter representations" (p. 94). Accordingly, in modern education, AI may be viewed as manifesting in both cognitive and social phenomena, such as through the application of intelligent tutoring systems to enhance student learning. Specifically, from a cognitive perspective, AI-based tutoring systems can analyze student responses, identify learning patterns, strengths, and areas for improvement, and then personalize educational content to maximize students' learning engagement and understanding (e.g., Bonneton-Botté et al., 2020; de Castro Rodrigues et al., 2022). From a social perspective, AI can facilitate collaborative educational environments and learning experiences by enabling students to interact with one another and with virtual assistants (e.g., Aeschlimann et al., 2020; Girouard-Hallam & Danovitch, 2022).

At the time of this writing in 2023, although the term "AI" has existed for nearly seven decades since McCarthy et al. (1955) coined it, it has only been in the past two decades that researchers (e.g., Addessi & Pachet, 2005; Aeschlimann et al., 2020; Su & Yang, 2023; Xu, Aubele et al., 2022) have begun examining AI applications in early childhood education. The term, *early childhood education,* has been defined variously across countries and regions. In the United States, early childhood education is referred to as the provision of educational programs and services to young children (ages birth to 8 years) (NAEYC, 2020). This scoping review adopted NAEYC's (2020) definition of early childhood education. As children are increasingly surrounded by AI technologies and tools, research is needed to scope the empirical literature to determine the global landscape of the current state of knowledge concerning AI use in early childhood education. Such a scoping review is, thus, timely and highly relevant. Currently, there exist two reviews (Crescenzi-Lanna, 2023; Su & Yang, 2022) that examined AI in early childhood education. However, as discussed later in this article, there are concerns about the rigor and clarity of their study selections.

To address the limitations of the two existing reviews, I endeavored to offer a more rigorous scoping review on a similar topic. A scoping review is considered a type of "knowledge synthesis" that systematically identifies and summarizes an existing or emerging body of literature on a specific topic of interest (Arksey & O'Malley, 2005; Mak & Thomas, 2022; Tricco et al., 2016). Accordingly, this scoping review sought to achieve three main goals: (1) "mapping" the global landscape of the current extent, range, and nature of relevant studies concerning the affordances of AI for use in early childhood education, (2) identifying potential research gaps, and (3) charting future research directions. Given that *scoping review* is considered synonymous with *scoping study*, which is referred to as an "approach to reviewing the literature" on a given topic (Arksey & O'Malley, 2005, p. 21), this article uses these two terms interchangeably.

2. The Theory of Affordances

In this scoping study, I focused particularly on the various affordances that AI can offer within the context of early childhood education. The concept, "affordances," was first introduced by Ecological Psychologist James J. Gibson (1979) to capture his ecological theory of perception as the organic interconnections between organisms and the *affordances* of the environment to them. Gibson posited that "things in the environment can be directly perceived" and "to perceive them is to perceive what they afford" with respect to their "values" and "meanings" (p. 127). Gibson's affordances theory implies a strong relationship between the direct perception and the affordances for action. In the context of this scoping review, I examined research studies specifically related to the educational benefits that AI has *afforded* young children, as revealed by existing research, and how these findings can better inform and advance the current state of knowledge in this area.

3. A Brief Historical Overview of the Evolution of AI

History indicates that humans have been continuously inventing and utilizing a diverse range of technologies, from fire to the wheel to the computer to the Internet to AI and everything in between, to enable all facets of human civilization to not only survive but also thrive (Akata et al., 2020). These technological advancements and deployments demonstrate both the breadth and significance of technological evolution over time throughout human history. Notably, the technological field is constantly and rapidly advancing. Take AI for example, over the last few decades, it has undergone substantial transformations. As a case in point, AI has evolved beyond the traditional reliance on rule-based systems that require explicit programmed rules and predetermined instructions to perform tasks, to the invention and deployment of innovative advanced technologies to tackle complex tasks with greater flexibility and creativity (Akata et al., 2020).

In this new era of AI, which proliferates across the technological landscape, AI technologies and AI-powered tools have become increasingly ubiquitous in many aspects of life and nearly all sectors of society. For instance, advanced technologies have been adopted in sectors, such as healthcare (Topol, 2019), and education (Crescenzi-Lanna, 2023). Particularly in recent years, education – as a major sector in society – has also been increasingly transformed by the affordances of AI for achieving a range of tasks, from assessing student learning to personalizing or differentiating instruction (e.g., Chen & Perez, 2023), using (AI)-interfaced robotic toys to help children acquire inquiry literacies (Kewalramani, Kidman et al., 2021), and promoting child-centered education (Devi et al., 2022). As a result, education may be perceived as affording a unique and open field for the application of AI and the test of the potentiality of AI in transforming teaching and student learning.

With the prevalence of AI in our everyday lives and environments, it has become commonplace for individuals – including children – to use intelligent voice/virtual assistants (e.g., Apple's Siri, Amazon's Alexa, Google Assistant) as AI-powered tools for achieving various functions, such as navigation, information retrieval, and personal reminders. Many also use chatbots (e.g., ChatGPT, the travel chatbot Octa) that rely on AI's capacities to understand spoken or written commands, requests, or questions by the user and perform tasks accordingly (Chen & Lin, 2024). In essence, today's children are growing up in an increasingly AI-infused world surrounded by the proliferation and accessibility of AI technologies and AI-powered tools (Axell & Berg, 2023; Chen & Lin, 2024).

4. AI Technologies and Tools

AI is a broad term that refers to systems that imitate, stimulate, and even surpass human capacities in solving complex real-world problems (e.g., Abbass, 2021; Calo, 2017; Ludger, 2009; McCarthy, 2007). These systems can be distinguished into two groups: (1) AI as technology, and (2) AI as a tool. AI as technology refers to the broader domain of knowledge and techniques (e.g., machine learning algorithms, neural networks, natural language processing) used to power AI systems or tools, enabling them to mimic human cognitive abilities and making them more intelligent in performing and adapting to complex tasks (Calvert, 2021; Erbeli et al., 2023; Kim et al., 2022; Xu, Vigil et al., 2022). AI as a tool refers to the software applications or systems that are powered by AI technology, and thus, may be referred to as AI-powered tools. For succinctness, hereinafter, AI-powered tools are simply referred to as AI tools.

5. Tangible and Intangible AI Tools in Early Childhood Education

Within the technological realm, AI-powered systems and tools can be categorized into two design categories: (1) tangible, and (2) intangible. Tangible AI systems and tools (e.g., robots, robotic toys) are physical entities that leverage AI technologies in a physical form designed and programmed to accomplish specific tasks by being controlled autonomously or by humans (e.g., Hsiao et al., 2015; Kewalramani, Kidman et al., 2021 Kewalramani, Palaiologou et al., 2021). On the other hand, intangible AI systems and tools do not possess a physical form but are embedded in intelligent agents, such as virtual assistants (e.g., Aeschlimann et al., 2020; Girouard-Hallam & Danovitch, 2022), and conversational agents (e.g., Xu, Aubele et al., 2022; Xu, Vigil et al., 2022; Xu, Wang et al., 2021). These intangible tools are integrated with AI technologies, thereby enhancing their functionality to enable interaction with humans and their environments.

5.1. Tangible AI Robots

As technological trends evolve, there's a noticeable shift in innovation from basic applications (e.g., remote-controlled toys) toward more advanced AI applications (e.g., intelligent/smart robotic toys). Reflecting this technological advancement, we have witnessed in recent years a surge of tangible smart robotic toys and robots that are developmentally appropriate and engaging for children (Akdeniz & Özdinç, 2021; Wang et al., 2021; Williams et al., 2019). Wang et al. (2021) defined a smart toy "as the integration of traditional toys and intelligent technology such as speech synthesis, artificial reality, and machine vision to interact with children" (p. 151). These smart toys can be designed and deployed to facilitate children's learning and development. For instance, Wang et al. (2021) integrated both human intelligence and AI in designing intelligent companion toys to help enhance preschool children's cognitive development. Akdeniz and Özdinç (2021) created an interactive humanoid robot named "Maya," which was programmed as an intelligent tutoring system to support preschool children's learning of basic concepts (numbers, shapes, animals, and colors) at their own pace and with teaching strategies catered to their learning needs.

5.2. Tangible and Intangible Conversational Agents

Conversations with others are vital for children's learning in the early years, especially in language development (Chen & de Groot Kim, 2014). Traditionally, children's conversational partners have only been humans (e.g., parents, teachers, peers). With advanced technologies, children's conversational partners have been extended to include AI that has the natural language processing capabilities to become conversational agents for children (Xu, 2023; Xu, Aubele et al., 2022; Xu, Wang et al., 2021). Conversational agents are integrated with various properties, including those with embodiment (e.g., robots) and those without (e.g., voice assistants) (Lee et al., 2006). Embodied intelligent systems are those designed to have a tangible physical presence to interact with humans and navigate the physical world like humans do. In contrast, non-embodied intelligent systems are intangible as they are not designed to interact with humans in a physical form. In reviewing the literature on the possibility of conversational agents (tangible and intangible) as social partners for children, Xu (2023) concluded that these technologies could encourage children to interact with, trust in, and learn from them as social partners.

5.3. Intangible AI Technologies for Predicting/Classifying Children's Conditions

Advanced technologies, such as machine learning and learning analytics, that use algorithms to analyze data collected about children in various forms (e.g., audio, visual, biometric on wristbands, performance analytics, eye tracking) along with human intervention can be particularly useful in early childhood education because of their adaptive nature (Crescenzi-Lanna, 2020, 2023). These technologies can uncover patterns of children's behavior and train AI models to analyze the data and personalize learning tasks to enhance these children's performance accordingly (Crescenzi-Lanna, 2023). Studies (e.g., Carpenter et al., 2016; Erbeli et al., 2023, Justice et al., 2019; Kim et al., 2022) have examined the use of AI technologies to predict children's risk for developing various disorders. To illustrate this AI application, Chen and Perez (2023) detailed the capabilities of an AI tutor system named "Amira." This system can amass, process, and analyze extensive amounts of data to identify patterns in children's reading progress and performance to make decisions on personalized learning experiences for English-Spanish bilingual children and predict their risk for dyslexia.

5.4. Learning About AI

To encourage children's development of AI competencies, AI education and curriculum have been implemented (Su & Zhong, 2022; Williams, Park, Oh et al., 2019; Yang, 2022). For example, Williams, Park, Oh et al. (2019) created "PopBots," a hands-on AI toolkit and curriculum that was designed to facilitate children's learning by doing (i.e., learning about AI by engaging in programming, training, and interaction with a social robot). Kewalramani, Palaiologou et al. (2021) also found that children learned about AI by engaging with them, such as interacting with social robots programmed to provide social and emotional support to children. Furthermore, Crescenzi-Lanna's (2023) literature review highlights the need to help children develop AI competencies starting from preschool and going beyond just general computational thinking skills to fostering understanding of key AI concepts to become AI literate.

6. The Significance of this Scoping Review

As mentioned in the introduction of this article, in reviewing the current literature, I found two existing reviews (Crescenzi-Lanna, 2023; Su & Yang, 2022) about AI in early childhood education. However, I have concerns about each one of them. Regarding Crescenzi-Lanna's (2023) literature review, the researcher selected 39 research papers for inclusion but did not list them nor supply descriptive details about them. Consequently, these articles could not serve as a point of reference for comparison or cross-checking the researcher's findings and related interpretations.

While Su and Yang (2022) seemed to have conducted an exhaustive search, which yielded 17 publications for review on AI in early childhood education. Their articles were inclusive of various natures (journal articles, conference proceedings, and a book chapter) from different countries. A main concern regarding Su and Yang's (2022) scoping review is the lack of strict adherence of their article selection to their inclusion/exclusion criteria. For instance, they stated that their third criterion involved the exclusion of "papers that participants or settings not 3–8 years old (n = 3)" (p. 3.). However, Su and Yang included some articles that should have been excluded according to this exclusion criterion. For instance, Su and Yang did not exclude Vartiainen et al.'s (2020) study even though it included 9-year-olds as participants. They also did not exclude the studies by Druga et al.'s (2019) and by Druga and Ko's (2021), even though both included children ages 7-12 years. Similarly, Su and Yang also did not exclude Tseng et al.'s (2021) study on children ages 8-14 years.

Furthermore, Su and Yang included Ge et al.'s (2021) study involving "2842 teachers," which would warrant exclusion according to the third exclusion criterion they established.

The aforementioned concerns regarding the two existing scoping reviews prompted me to conduct a more rigorous scoping study on a similar topic, thereby contributing additional knowledge to the field of AI in early childhood education. Specifically, as shown in Table 1, the nature of this scoping review differed from that of Crescenzi-Lanna (2023), and of Su and Yang (2022) in terms of the specific topic of interest, the publication years of the reviewed articles, the databases used to locate the relevant articles, the number of articles reviewed, and the main findings. For instance, one noticeable difference between this scoping review and Su and Yang's (2022) was study selection. Specifically, among the 17 included articles in Su and Yang's (2022) scoping review, most of them (12) were conference proceedings. In contrast, I focused only on pertinent research articles in peer-reviewed academic journals, resulting in 18 of them being included.

Table 1. Comparison of the current scoping review with the existing two reviews concerning AI in early childhood education.

Author(s) (year)	Chen (2024)	Crescenzi-Lanna (2023)	Su & Yang (2022)
Title of Article	The current study: "A Scoping study on AI affordances in early childhood education: Mapping the global landscape, identifying research gaps, and charting future research directions"	"Literature review of the reciprocal value of artificial and human intelligence in early childhood Education"	"Artificial intelligence in early childhood education: A scoping review"
Publication Outlet	*Journal of Artificial Intelligence Research*	*Journal of Research on Technology in Education*	*Computers and Education: Artificial Intelligence*
Research Type	Scoping Review	Systematic Literature Review	Scoping Review
Topic of Interest	The affordances of AI for use in early childhood education	The "reciprocal contributions" of humans and AI in teaching and learning in early childhood education	AI in early childhood education in the areas of research design, AI tools, AI activities, and findings
Educational Level of Reviewed Articles	Early Childhood Education	Early Childhood Education	Early Childhood Education
Publication Years of Articles Reviewed	1955-2023	2018-2022	1995-2021
Databases	• ERIC • PsycINFO • Academic Search Premier	• Web of Science • Scopus	• Web of Science • ERIC • EBSCO • IEEE • Scopus
Number of Articles Reviewed	18 research articles from 11 countries, published in 16 peer-reviewed academic journals	39 papers (neither listed nor provided with individual information about each one)	17 articles (4 research articles, 12 conference proceedings, and one book chapter) from various countries

Author(s) (year)	Chen (2024)	Crescenzi-Lanna (2023)	Su & Yang (2022)
Main Findings/Conclusion	Affordances of AI for use in early childhood education: (1) AI as tangible and intangible tools for interactive learning and information retrieval (2) AI as technologies for predicting/ classifying children's conditions (3) AI as the object for learning by adapting to and personalizing learning for children (4) AI as the subject for children's learning about it	Advanced technologies in early childhood education research (e.g., artificial intelligence, machine learning, learning analytics) are both a learning objective and a method for collecting and/or analyzing data related to preschool education" (p. 23).	AI benefited children's learning about AI-related concepts, such as machine learning, computer science, and robotics, as well as other skills.

7. Method

This scoping study endeavored to map the global landscape of the current state of knowledge on the affordances of AI for use in early childhood education, thereby identifying research gaps for future empirical ventures. To this end, I conducted a scoping review of all available and relevant empirical literature. To ensure that this process was "rigorous and transparent," I adhered to Arksey and O'Malley's (2005)'s methodological framework involving a process of five stages: (1) "identifying the research question," (2) "identifying relevant studies," (3) "study selection," (4) "charting the data," and (5) "collating, summarizing and reporting the results" (p. 22).

7.1. Stage 1: Identification of the Research Questions

The very first imperative stage of conducting a scoping study is identifying a research question, one that will serve as a "roadmap" guiding subsequent stages (Levac et al., 2010). This research question needs to be both deep and broad enough to ensure a comprehensive coverage of available relevant literature (Arksey & O'Malley, 2005; Levac et al., 2010). For this scoping study, I investigated this overarching research question: *What is the global landscape of the current state of knowledge concerning the affordances of AI for use in early childhood education?* Specifically, the *state of knowledge* here refers to three aspects: (1) extent, (2) range, and (3) nature. Furthermore, three corresponding sub-questions were formulated:

(1) What is the extent of research studies that have been conducted related to the affordances of AI for use in early childhood education?
(2) What is the range of research studies that have been conducted related to the affordances of AI for use in early childhood education?
(3) What is the nature of research studies that have been conducted related to the affordances of AI for use in early childhood education?

Guided by these research questions, this scoping review sought to "map" the available relevant literature and "chart" the topography of the affordances of AI for use in early childhood education.

7.2. Stage 2: Identification of Pertinent Research Studies

To achieve both depth and breadth in outcomes, we (the author and her graduate research assistant) identified all pertinent empirical studies, regardless of research design, method of data collection, and country of origin, in order to "paint" a comprehensive, global landscape of this focused topic.

We began this process by conducting a meticulous literature search in three major electronic databases: (1) Academic Search Premier, (2) ERIC, and (3) PsycINFO. These databases were selected because they were considered prominent in the fields of education and psychology. They have also demonstrated success in previous literature searches on other topics (e.g., Chen, 2023, 2024).

Aligning with the research questions for this study, we set our search parameters to two broad terms ("artificial intelligence" AND "early childhood education or early childhood or early years") separated by the Boolean operator "AND." The results of our literature search (e.g., the exact number of records retrieved from each database, each step of the study identification process leading to the final selection of studies for inclusion) are detailed in the Preferred Reporting Items for Systematic Reviews extension for Scoping Reviews (PRISMA-ScR) flow diagram (see Figure 1), which was adapted from Page et al.'s (2021) template. As summarized in Figure 1, a search of the three databases yielded a total of 188 records. After removing 15 duplicates, we retained 173 articles for initial screening. We then independently performed the initial screening of these 173 articles by culling through their titles and abstracts. This process resulted in only 25 of these articles being deemed eligible for further screening. To ensure search fidelity, we replicated the same procedure, which yielded the exact result.

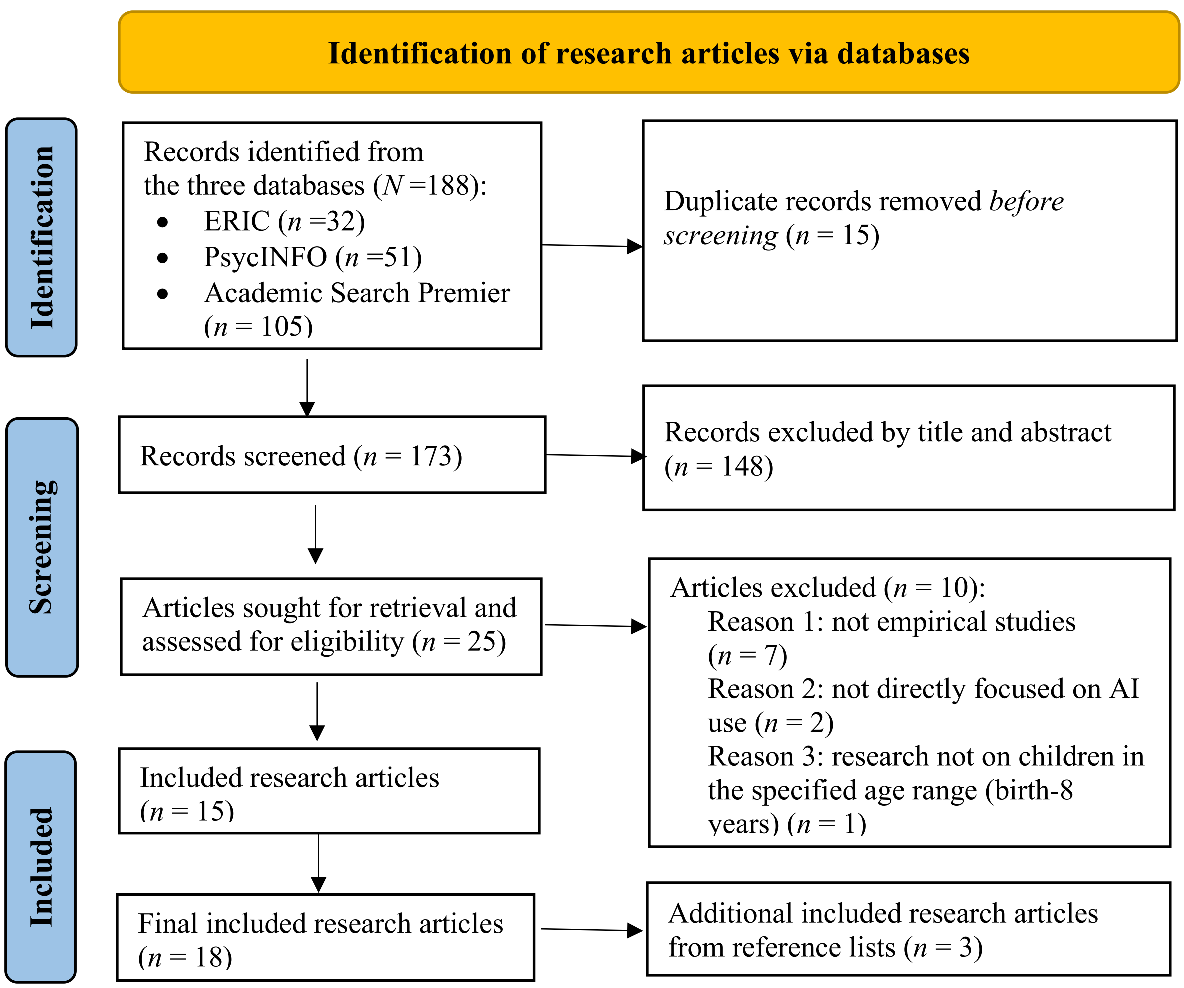

Figure 1. PRISMA-ScR flow diagram for included empirical articles in the scoping review.

7.3. Stage 3: Selection of Pertinent Research Studies

After identifying the 25 empirical articles, we proceeded to locate and read their full texts to further determine their eligibility. To guide this process, we first established seven inclusion and exclusion criteria (see Table 2) and then applied them to select eligible articles from the initial pool of 25. First and foremost, given that this scoping review focused on empirical literature, we included only research articles and excluded all others. Second, aligning with the aforementioned definition of early childhood education as serving children (from birth to age 8) (NAEYC, 2020), this scoping review included only research studies involving data about children within this age range and excluded those about older age groups. We adopted NAEYC's age designation for children in early childhood education due to its broader age range of up to eight. We recognized that in other geographical contexts, early childhood education is limited to a younger upper age limit. For instance, the designation of early childhood years in China (Li & Chen, 2023) and Hong Kong (Chen et al., 2017; Chen et al., 2024) extends up to only age six.

Third, for the purpose of this scoping review, only empirical studies related to AI use in early childhood education were deemed “fit” for inclusion. Fourth, only those published in peer-reviewed academic journals were included, as the refereed process is regarded as a standard quality control by the research community in the fields of education, psychology, and others. Fifth, the inclusion criterion did not limit publications to only those written in English so that we may cast a wider global net to include relevant articles published in a non-English language. This inclusive approach led to two articles written in a non-English language (one in Chinese and the other in Spanish). However, upon reviewing their translated abstracts in English, we determined that the article in Chinese was not related to AI and the article in Spanish was not based on an empirical study. Thus, these two articles were subsequently excluded. Sixth, since the empirical studies would serve as the unit of analysis, it was imperative that their full texts (electronic or print) were locatable for subsequent reading and evaluation. Finally, the seventh criterion stipulated that we would include only research articles published between 1955 (when the term, *artificial intelligence (AI)*, was first coined by McCarthy et al.) and August 2023 (when the article searches for this scoping study were conducted).

Table 2. The inclusion and exclusion criteria for selecting relevant research articles related to the affordances of AI for use in early childhood education.

Criterion	Inclusion	Exclusion
(1) Type of article	Empirical studies	Non-empirical studies (e.g., literature review, practical, theoretical)
(2) Research participants	Children (ages birth to 8 years)	Inclusion of children older than eight years
(3) Research focus	AI-related	Not AI-related
(4) Research method	Any	None
(5) Publication outlet	Empirical studies published in peer-reviewed academic journals	Empirical studies not published in peer-reviewed academic journals or published in the gray literature (e.g., books, book chapters, conference proceedings, documents, reports, theses/dissertations); non empirical studies.
(6) Language of article	Any	None
(7) Year of publication	1955 to 2023	Articles outside of this timeframe

A careful examination of the electronic texts of the initial 25 eligible articles resulted in 10 of them being excluded (see Figure 1). The subsequent process led to the final selection of 15 relevant empirical articles for inclusion. Furthermore, we also applied the "snowball" search method by scanning reference lists of included articles for potential studies, a process that yielded three additional research articles for inclusion. As a result, a final total of 18 relevant empirical articles was included in this scoping review.

7.4. Stage 4: Charting of Data

After selecting the relevant research articles for inclusion, the next stage entails "charting" the data (Ritchie & Spencer, 1994) by identifying embedded key concepts, themes, or items of information (Arksey & O'Malley, 2005). In this study, the charting process involved recording the extracted data into "data charting tables" (see Table 3a and Table 3b) according to the following:

- Author(s) (Year of Publication)
- Study Country
- Study Aim(s)
- Definition, Type, and Purpose of using AI
- Study Type
- Study Population
- Data Collection
- Main Findings
- Main Implications

My graduate research assistant and I independently coded the data by extracting the essential information according to this coding scheme. Since the charted data (see Table 3a and Table 3b) between us were similar, we felt confident using them as the foundation for subsequent analyses.

Table 3a. Data charting of the included research studies ($N = 18$) related to the affordances of AI for use in early childhood education.

Author(s) (Year of Publication)	**Study Country**	**Study Aim(s)**	**Definition, Type, and Purpose of Using AI**	**Study Type**	**Study Population**
Addessi & Pachet (2005)	Italy	To investigate "how the use of *interactive musical systems* can affect the learning and the musical creativity" of young children (p. 13).	**Definition of AI:** Not provided. **AI technology used:** *"Interactive musical systems"* named Continuator, an AI innovative system that is interactive and reflective in nature creates "music in the same style as the person playing the keyboard" (p. 13). **The purpose of using AI:** ***Adaptive learning*** To assist children in learning music and developing musical creativity.	Experimental	27 children (ages 3-5) in a kindergarten
Aeschlimann et al. (2020)	Switzerland (not specified but inferred from the authors' country of affiliation)	To investigate the communication patterns and prosocial behaviors of children when interacting with voice assistants.	**Definition of AI:** Not provided. **AI technology used:** *Voice assistants* **The purpose of using AI:** ***Social interaction*** To assess children's interaction with voice assistants.	Experimental	72 children (ages 5-6)

Author(s) (Year of Publication)	Study Country	Study Aim(s)	Definition, Type, and Purpose of Using AI	Study Type	Study Population
Bonneton-Botté et al. (2020)	France	To assess the effect of a digital notebook application on kindergarten children's handwriting learning by using AI to analyze their handwriting's spatiotemporal characteristics as a basis to provide personalized practices and extrinsic feedback.	**Definition of AI:** Not provided. **AI technology used:** *A digital handwriting notebook app on a stylus-oriented tablet* **The purpose of using AI:** ***Adaptive learning*** Using AI as a tool to analyze the handwriting of children to provide real time, personalized feedback concerning different aspects including shape, direction, and stroke order. For instance, the app's AI checks whether the child has completed a handwriting task successfully and if not, provides a simplified task.	Experimental	233 children (ages 5-6) from 22 preschools
Carpenter et al. (2016)	United States	To test whether individual items or groups of items from the Preschool Age Psychiatric Assessment (PAPA) would predict generalized anxiety disorder (GAD) and separation anxiety disorder (SAD) in children.	**Definition of AI:** Not provided. **AI technology used:** *Alternating decision trees algorithm* (a machine learning technique for classification) **The purpose of using AI:** *Prediction: Assistance with diagnosis* To predict the likelihood of a child having GAD or SAD.	Qualitative (parent interviews) and Quantitative (parent questionnaire, assessments)	1,124 children (ages 2-5): 307 in Study 1 and 917 in Study 2, and their parents
de Castro Rodrigues et al. (2022)	Brazil	To test the effectiveness of the application of AI techniques to educational games with letters that can build self-adjusting intelligent interfaces based on the player's profile in the game to enhance the children's literacy learning.	**Definition of AI:** Not provided. **AI technology used:** *AI-powered educational games* **The purpose of using AI:** ***Adaptive Learning*** The AI techniques adjust to the user's needs in real time to help enhance children's literacy learning through educational games.	Experimental	62 children (ages 3-4) divided into two equal groups
de Haas et al. (2022)	The Netherlands	To investigate potential differences in children's task engagement and robot engagement during English learning tutoring sessions in different experimental conditions.	**Definition of AI:** Not provided. **AI technology used:** *Peer-Tutor Robot for Language Learning* **The purpose of using AI:** *Language learning and social interaction* To investigate the effects of the different types of peer-tutor robot interactions on children's English language learning.	Experimental	194 native Dutch-speaking children (averaging 5 years and 8 months) from nine different Dutch primary schools
Erbeli et al. (2023)	United States	To compare the prediction performance of random forest, a machine learning technique, to the traditional logistic regression method.	**Definition of AI:** Not provided. **AI technology used:** *Machine learning algorithms* **The purpose of using AI:** ***Prediction*** To determine the effectiveness of random forest, a machine learning technique in determining risk for developing reading disabilities.	Quantitative	12,171 third graders were determined at risk for reading disabilities by four indicators in the first and second grade.

Author(s) (Year of Publication)	Study Country	Study Aim(s)	Definition, Type, and Purpose of Using AI	Study Type	Study Population
Girouard-Hallam & Danovitch (2022)	United States	To investigate "children's trust in and recall of statements made by a novel voice assistant and a human informant" (p. 646)	**Definition of AI: Not provided.** **AI technology used:** *voice assistant* **The purpose of using AI:** *Informational retrieval* To examine the extent of children's trust in using the voice assistant for information as well as recall of information provided.	Quantitative (children responding to a series of questions asked verbally by the experimenter)	**Two studies:** The same number of children in the same age brackets participated in each study, with 80 children in total: 40 children (ages 4-5) and 40 children (ages 7-8) from mostly White, upper middle-class families.
Gulz et al. (2020)	Sweden	To investigate the ways in which preschool children made sense of critical information in a digital game based on a teachable agent designed to support early math development and perceive the teachable agent as an agentic entity that has the ability to act in an independent and goal-directed way, facilitated by its own knowledge.	**Definition of AI: Not provided.** **AI technology used:** *Teachable agent* **The purpose of using AI:** *Learning by teaching an intelligent agent* Applying the "learning-by-teaching" pedagogical approach, children learn by teaching a "digital tutee"/teachable agent early math.	Experimental	36 children (ages 4-6)
Hsiao et al. (2015)	Taiwan	To investigate the influence of an intelligent robot, named iRobiQ, as a learning companion on children's reading ability, interest, and performance in comparison to learning using a tablet-personal computer (PC).	**Definition of AI: Not provided.** **AI technology used:** *An intelligent robot (named iRobiQ) was employed as a language teaching/learning tool and companion* **The purpose of using AI:** ***Robot as a learning companion*** To enhance children's reading ability, interest, and behavior by leveraging multimedia contents to attract and encourage them to read, talk, and answer questions as a way to help improve children's reading ability and interest as well as learning behavior.	Experimental	57 children (ages 2-3) from similar backgrounds in pre-kindergarten in Taipei and New Taipei, Taiwan
Justice et al. (2019)	United States	To leverage machine learning to help identify variables that would best classify children having language disorder therapy.	**Definition of AI:** Not provided. **AI technology used:** *Machine learning algorithms* **The purpose of using AI:** ***Prediction/Classification*** To identify the variables that would best classify children receiving language disorder therapy.	Intervention	483 children (ages 3-5; 54% of whom were affected).

Author(s) (Year of Publication)	Study Country	Study Aim(s)	Definition, Type, and Purpose of Using AI	Study Type	Study Population
Kewalramani, Kidman et al. (2021)	Australia	To investigate "how the children participate, engage, inquire and interact with the robotic toys and how this shapes their inquiry literacy" (p. 657).	**Definition of AI:** Not provided. **AI technology used:** *AI robotic toys for young children to play with* **The purpose of using AI:** ***Learning companion*** To intentionally leverage AI-interfaced robotic toys for children to play with to foster their inquiry-driven literacies.	Qualitative (Observation and interview)	While stating that this study occurred in two kindergarten classrooms serving children (ages 4-5), the authors then clarified that the data reported in the article came from only one classroom comprising 21 children, 2 teachers, and 1 co-educator.
Kewalramani, Palaiologou et al. (2021)	Australia	To explore "whether and how technologies such as Artificially Intelligent (AI) toys in a home-based setting might socially and emotionally support children with diverse needs through play" (p. 1).	**Definition of AI: Not provided.** **AI technology used:** *AI robot* **The Purpose of using AI:** *As a social and emotional supportive agent* To promote children's social and emotional development.	Qualitative (observation and interview)	5 children (ages 4-7) with diverse special needs.
Kim et al. (2023)	South Korea	To compare the performance of classifying children in the autism spectrum disorder (ASD) group and those in the typically developing control group among five machine learning algorithms: (1) support vector machine (SVM), (2) logistic regression (LR), (3) random forest (RF), (4) AdaBoost, and (5) multi-layer perceptron (MLP).	**Definition of AI:** Not provided. **AI technology used:** *Machine learning algorithms* **The purpose of using AI:** ***Classification*** (1) To classify children with low-functioning autism spectrum disorder (LFA) children and those with typically developing controls (TDCs) by applying five machine learning techniques. **(2)** to determine whether multimodal data from both T1-weighted (T1w) magnetic resonance imaging (MRI) and diffusion tensor imaging (DTI) data is better than unimodal MRI data in the classification performance.	Quantitative	106 children (ages 3-6): 58 with ASD and 48 with TDC
Su & Yang (2023)	Hong Kong (a special administrative region of the People's Republic of China)	"to determine how an eight-week AI literacy program intervention affected young children's AI literacy, AI-related creativity, and perceptions of the AI4KG curriculum" (p. 3)	**Definition of AI:** Not provided. **AI technology used:** *(1) "AI for Oceans," (2) "Teachable Machine," and (3) "Quick, Draw!"* **The purpose of using AI:** *AI literacy learning* To promote children's development of AI literacy and AI-related creativity.	Intervention	26 children (ages 3-5) in two classrooms of a public kindergarten in Hong Kong

Author(s) (Year of Publication)	Study Country	Study Aim(s)	Definition, Type, and Purpose of Using AI	Study Type	Study Population
Xu, Aubele et al. (2022)	United States (not specified but inferred from the authors' affiliation and participants' information).	To investigate "whether a conversational agent can improve children's story comprehension and engagement, as compared to an adult reading partner" (p. e149).	**Definition of AI:** Not provided. AI technology used: An automated c*onversational agent system (the smart speaker from Google Home Mini Device)* **The purpose of using AI:** *Conversational interaction* to enhance story engagement and comprehension in children.	Experimental	117 children (ages 37-81 months, averaging 58.10 months)
Xu, Vigil et al. (2022)	United States	"to examine the impact of contingent interaction with artificially intelligent media characters in video watching on children's learning" (p. 3)	**Definition of AI:** Not provided. **AI technology used:** *AI media characters in video as conversational agents, leveraging natural language processing.* **The purpose of using AI:** *Social interaction/learning companion t*o enhance science learning and engagement	Experimental	77 children (ages 4-6)
Xu, Wang et al. (2021)	United States	To compare the effectiveness in supporting children's reading comprehension between a conversational agent and a human adult partner.	**Definition of AI:** Not provided. **AI technology used:** *An automated conversational agent (CA) system (the smart speaker from Google Home Mini Device)* **The purpose of using AI:** *Conversational interaction* To promote children's language development using an automated CA designed to simulate the natural flow of dialogue by a human conversational partner.	Experimental	90 children (ages 3-6)

Table 3b. Data charting of the included research studies (N = 18) related to the affordances of AI for use in early childhood education.

Author(s) (Year of Publication)	Data Collection	Main Findings	Main Implications
Addessi & Pachet (2005)	Children engaged in three sessions of playing on the keyboard per day for 3 consecutive days. During each session, the children engaged in four different music playing conditions: (1) with the keyboard only, (2) with the keyboard connected to the interactive musical systems, (3) with another child, and (4) with another child and the interactive musical systems.	AI technology benefited the children's learning and musical creativity. Specifically, the two tasks involving the interactive musical systems resulted in the longest attention span marked by high intrinsic motivation and joint attention, and various listening skills.	AI-based interactive music systems involving the interaction between the user and the system, such as the Continuator in this study, can help support children's development of meaningful child/computer interactions and creative musical behaviors. The findings demonstrate the didactic and adaptive benefits of using AI in music education.

Author(s) (Year of Publication)	Data Collection	Main Findings	Main Implications
Aeschlimann et al. (2020)	The 72 children were divided equally into four conditions (18 children in each) of a treasure hunt activity: "The conditions were a combination of the **interaction partner** (a human or a voice assistant) and the **information type** (knowledge or experience) during the treasure hunt, resulting in four between-subjects conditions (human – knowledge, human – experience, voice assistant – knowledge, voice assistant – experience)" (p. 3). Afterwards, children completed a prosocial task involving sharing with and helping others.	During the treasure hunt activity, children talked less and provided less information when interacting with the voice assistant than with the human. There was a difference in sharing behavior, with the type of information shared influencing the children's selection of information when interacting with a human. No differences in helping behavior were found.	Children clearly distinguished humans and voice assistants during interaction, assuming that voice assistants did not need the same information as humans. The findings suggest that children hold different expectations on voice assistants than humans, and that there are differences between children's cooperation with humans and that with voice assistants.
Bonneton-Botté et al. (2020)	The children participated in a 12-week intervention implemented by teachers. The children were grouped into two experimental conditions: 138 children in nine of the schools were in the digital group using a handwriting app on a tablet with a stylus, while the remaining 95 children in the non-digital group using the traditional paper and pencil for handwriting learning. All children completed a paper-and-pen writing exercise as a pre-test and post-test to assess whether there was growth as a result of the intervention.	Only children with an initial writing level as medium at the start of the study benefited from the training with the digital app.	The benefits of AI-powered tools may vary as a function of the characteristics of the learners, such as their initial level of graphomotor in this study.
Carpenter et al. (2016)	Data were collected from two independent studies: (1) the PAPA Test-Retest Study (*N* = 307), and (2) the Duke Preschool Anxiety Study (*N* = 917) of parents with children (ages 2-5) attending Duke University Pediatric Primary Care Clinics. Methods of data collection include assessments using a complete diagnostic interview with parents.	The machine learning algorithms-based screening trees was proven a validated approach to screening children for risk for generalized anxiety disorder and separation anxiety disorder in children.	Machine learning technology can be valuable in designing mental health screening tools that are practical and accessible for use in pediatric clinics and daycare/preschool settings. Early screening can facilitate early interventions and treatments.
de Castro Rodrigues et al. (2022)	An educational game for mobile devices designed to help children acquire literacy with AI techniques for the intervention group. Data collection included game usage directly from each participant's device.	Children who used the AI approach performed better than those who did not. These children achieved more positive learning outcomes in terms of characteristics observed (e.g., the number of hits/correct answers to questions asked related to letters identification, response time).	The application of AI techniques could help enhance children's learning, such as letter identification as found in this study.

Author(s) (Year of Publication)	Data Collection	Main Findings	Main Implications
de Haas et al. (2022)	This study was part of a large-scale longitudinal study investigating the effectiveness of a peer-tutor robot on children's learning English as a second language (L2). The experiment consisted of pre-test, seven tutoring sessions, an immediate post-test, and a delayed post-test. The children were assigned to one of the four conditions for tutoring sessions for English learning: "(1) an L2 tutoring training with a tablet and a robot using iconic gestures (gestures that act out the meaning of a word) and deictic gestures (pointing gestures), (2) an L2 tutoring training with a tablet and a robot using deictic gestures, (3) an L2 tutoring training with a tablet, and (4) a control condition in which children danced with the robot but were not taught any English words." (p. 4)	Over time, the robot's iconic gestures did not influence children's task engagement, but it did affect children's robot engagement. Children were more engaged with a robot having iconic gestures than with one having no such gestures. Task engagement in all three experimental conditions and robot engagement in the two conditions with a robot (one with iconic gestures and one without), all positively predicted increase in English word retention after the tutoring sessions.	Robot's behavior, such as the various features on children's task engagement and robot's engagement in child-robot interactions, could influence English language learning over time.
Erbeli et al. (2023)	Collected data from all measures (e.g., the Dynamic Indicators of Basic Early Literacy Skills, the operational classification definition of RD risk, the Florida comprehensive assessment test – reading, the Peabody picture vocabulary test) were analyzed using machine learning techniques.	Results indicate that logistic regression and random forest, both of which are classification algorithms, produced equally accurate determination of risk for reading disabilities with multiple linear predictors.	Both logistic regression and random forest could be employed to accurately predict reading disabilities within school and clinical settings.
Girouard-Hallam & Danovitch (2022)	**Study 1:** The children heard the voice assistant's and the human informant's responses to questions from multiple categories and to indicate their trust in the information provided. **Study 2:** The children responded to whether to rely on a vice assistant or human informant for correct information.	**Study 1:** With increasing age, children trusted the voice assistant more for factual information and the human more for personal information. Children tended to be better able to remember information believed to be accurate, whether it was given by the voice assistant or the human. **Study 2:** With increasing age, children exhibited greater preference to seek out the voice assistant for factual answers to "stable and transient" questions, while younger children sometimes preferred to consult the voice assistant to respond to personal questions. However, by ages 7-8, children almost always preferred the human informant over the voice assistant for personal questions.	When implementing voice assistants, it is important to consider children's age, and the type of information sought.

Author(s) (Year of Publication)	Data Collection	Main Findings	Main Implications
Gulz et al. (2020)	The children engaged in real-time behavior during a teachable agent-focused play-&-learn game. "In an experimental part of the study, the children's gaze behaviors were measured during 5 rounds of interaction with an experimental version of one of the sub-games" (p. 38)	The children gazed at the teachable agent more frequently when it took charge of the gameplay than when it did not, suggesting that the children understood that the teachable agent was an agentic entity that made decisions based on its own knowledge just like themselves.	Log data of game performance combined with eye-tracking data may help refine AI algorithms targeting adaptive individual feedback and scaffolding.
Hsiao et al. (2015)	The children were divided into two conditions by place of residence and school district: The experimental group comprised 30 children and the control group included 27 children The experimental group included iRobiQ in their reading in Mandarin Chinese, whereas the control group utilized a tablet-personal computer.	• iRobiQ was more effective than tablet-PC. • iRobiQ was a bidirectional companion when interacting with children (e.g., children could speak with iRobiQ and ask questions, and iRobiQ could provide feedback nonverbally by means, such as moving hands and making sounds). • iRobiQ could foster peer collaboration and competition among children in storybook reading with peers and with iRobiQ even more.	Bidirectional interactive Robots, such as the IRobiQ in this study, could encourage teachers to design more active and interactive learning environments, activities, and experiences for children.
Justice et al. (2019)	"Secondary analysis of data collected during a randomized controlled trial (RCT) of an early-literacy intervention" (p. 353). Machine learning techniques were utilized to identify variables that could best predict who among the children would receive language disorder therapy.	Machine learning was able to help identify several factors pertinent to children receiving language therapy services including being male, having severe cognitive impairment, experiencing poorer outcomes in functional communication skills, early literacy skills, and social skills, and exhibiting higher levels of challenging behaviors.	Machine learning's ability to classify children receiving language therapy services in educational settings may help identify factors involved in those with clinical language disorder.
Kewalramani, Kidman et al. (2021)	The data were collected over 10 weeks involving the integration of AI- interfaced robotic toys to engage children in play. Methods included video observations of AI-toy play experiences among children and educators, semi-structured interviews with educators, and informal chats with children.	Playing with AI robot toys facilitated children's acquisition of three types of inquiry literacies: (1) "creative inquiry," (2) "emotional inquiry," and (3) "collaborative inquiry."	AI robotic toys could serve as mediators for promoting children's development of inquiry literacy, and teachers should provide opportunities for children to play with AI-interfaced robotic toys as an integral part of the development process of inquiry literacy.
Kewalramani, Palaiologou et al. (2021)	Data were collected virtually via multiple methods: Zoom interviews with children and their parents, video observations of workshops introducing the use of robots, informal chats with children during the workshops, self-generated video observations of play experiences between the children and their parents, and children's drawings showing how they conversed with their AI robots about feelings.	By engaging with AI robot toys, children had the opportunity to develop and apply their social and emotional communication skills, which were further supported by their interactions with adults and others.	AI robotic technologies may serve as valuable resources for helping children, especially those with special needs, develop social and emotional competence. However, these AI technologies cannot and should not be treated as a replacement for the role that humans (e.g., educators, parents) play in this endeavor. An optimal outcome would be to integrate these robotic technologies with human interventions.

Author(s) (Year of Publication)	**Data Collection**	**Main Findings**	**Main Implications**
Kim et al. (2023)	The five machine learning techniques (SVM, LR, RF, AdaBoost, and MLP) were employed to analyze the magnetic resonance imaging (MRI) and diffusion tensor imaging (DTI) data collected of these children.	• Analysis of MRI data using machine learning techniques proved useful in classifying low-functioning ASD children from TDCs. • The RF classifier performed the best in accuracy, sensitivity, and specificity, while LR performed the worst in accuracy and sensitivity, and SVM in specificity. • Multimodal data helped improve classification accuracy.	Machine learning techniques are effective for classification performance. Multimodal data are more effective and precise than unimodal data in identifying LFA preschoolers.
Su & Yang (2023)	The children participated in an AI literacy intervention after school weekly for 30 minutes over a span of eight weeks. The intervention was based on the A14KG curriculum. All activities were observed and videotaped.	• Young children had the ability to acquire basic AI concepts and related knowledge. • Younger children used their imagination to design a chatbot, while older children created an AI robot to assist with drawing. • Older children engaged in training AI using the tools, while younger children preferred other activities, such as drawing a future AI city and participating in AI storytelling.	Engaging children in AI literacy education could help prepare them for an AI-proliferated future.
Xu, Aubele et al. (2022)	The children were randomly assigned into one of the four experimental conditions: • "*Agent Dialogic Reading (Agent DR)* where the agent narrated the story to a child and engaged the child in dialogue by asking questions and providing feedback. • *Agent Non-Dialogic Reading (Agent Non-DR)* where the agent merely narrated the same story to a child but did not ask any questions to engage the child in dialogue. • Human Dialogic Reading (Human DR) where an adult narrated the story to a child and engaged the child in dialogue by asking questions and providing feedback. • Human Non-Dialogic Reading (Human Non-DR) where an adult merely narrated the same story to a child but did not ask any questions to engage the child in dialogue." (p. e153)	The conversational agent (agent dialogic reading condition) facilitated language development in children by engaging them in dialogic reading, which yielded the same benefits as an adult partner scaffolding story comprehension in children.	Given their affordability and prevalence in children's homes, conversational agents could serve as a potentially cost-effective AI-powered tool for facilitating young children's early literacy development. While leveraging these conversational agents' ability to effectively engage children in dialogic reading by integrating them into homes as an important aspect of informal learning experiences for these children, they should not supplant the role of adults (e.g., parents, teachers) as engaging human dialogic agents.

Author(s) (Year of Publication)	Data Collection	Main Findings	Main Implications
Xu, Vigil et al. (2022)	The children were "assigned to either the ***experimental condition*** in which children had contingent interaction with the show's main character as they watched the episode or the ***control condition*** in which children watched the same episode but without the opportunity for contingent interaction with the character" (p. 3). In the experimental condition where AI-assisted conversational interaction about science occurred, children answered questions asked by and received responsive feedback from the main character as the conversational agent.	Children in the experimental condition showed better learning outcomes (e.g., understanding the science concepts introduced in the conversational video better, showing more positive affect (e.g., smile), more positive of the media character) than those in the control condition.	High-quality programming could benefit children, such as by leveraging AI technologies to facilitate interaction with AI-powered on-screen media characters to promote learning and engagement.
Xu, Wang et al. (2021)	The children were randomly assigned to one of the three conditions: (1) **"Human Story"** where children listened to a story read by a human partner with no guided conversation, (2) **"Human-Conversation"** where children listened to a story read by a human partner with guided conversation, and (3) **"CA-Conversation"** where children listened to the same story read by a CA with guided conversation.	The guided conversation by the CA was as effective as that by a human partner in promoting story comprehension. However, there were differences in the children's responses to questions by the CA and those by the human partner (e.g., high cognitive demands questions from human partners elicited longer and more lexically varied responses).	Three main important implications for designing more effective CAs: (1) Be guided by a theoretical rationale for meeting the unique developmental and learning needs of children. (2) Focus on CA's conversation capacity and strengths to overcome its limitation in non-verbal expressions. (3) Recognize the unique properties of CAs as valuable tools.

7.5. Stage 5: Collation, Summarization, and Reporting of Findings

After charting the relevant data extracted from the included empirical studies, I proceeded to conduct a descriptive analysis by systematically summarizing the key themes and content within the data. In the process, I applied three strategies: (1) creating data displays, (2) crafting narrative summaries, and (3) conducting thematic analysis. First, I created visual representations in the form of tables to organize and summarize the charted data. These representations offered both quantitative and qualitative analyses of the extent, range, and nature of the affordances of AI for use in early childhood education. Second, I crafted descriptive narratives by summarizing the main findings of the data displays. Third, I employed Braun and Clarke's (2006) thematic analysis method by identifying inductively emerging themes and concepts within the charted data. I followed Braun and Clarke's six systematic steps of thematic analysis: (1) "Familiarizing yourself with your data," (2) "Generating initial codes," (3) "Searching for themes," (4) "Reviewing themes," (5) "Defining and naming themes," and (6) "Producing the report" (p. 87). After identifying the themes within the charted data of each research article, I then compared these themes across all included articles. It is important to note that I did not assess the methodological quality of the included studies, as that would go beyond the purview and purpose of this scoping review. However, for context, I provided specific details about each study, such as the research populations and data collection methods.

8. Results

The results are presented in the order of the three sub-research questions (RQs).

RQ1: *What is the extent of research studies that have been conducted on the affordances of AI for use in early childhood education?*
This question was addressed using numerical information concerning the number of research articles published on the topic, the academic journals in which they were published, the years of publication, and the countries where the studies were conducted.

8.1. The Number of Research Articles Included

As tabulated from the number of articles listed in Table 3a and Table 3b, the extent of the empirical literature related to the affordances of AI for use in early childhood education revealed only 18 research articles published in peer-reviewed academic journals.

8.2. The Academic Journals Containing Included Research Articles

As summarized in Table 4, the 18 included empirical articles were published across 16 peer-reviewed academic journals. With the exception of two academic journals (*Computers & Education*, and *Interactive Learning Environments*), each containing two research articles, the remaining journals each included only one article.

Table 4. Peer-reviewed academic journals publishing the included research articles (*N* = 18) related to the affordances of AI for use in early childhood education.

Author(s) (Year of Publication)	Name of the Academic Journal
Addessi & Pachet (2005)	*Musicae Scientiae*
Aeschlimann et al. (2020)	*Computers in Human Behavior*
Bonneton-Botté et al. (2020)	*Computers & Education*
Carpenter et al. (2016)	*PLoS ONE*
de Castro Rodrigues et al. (2022)	*Displays*
de Haas et al. (2022)	*International Journal of Child-Computer Interaction*
Erbeli et al. (2023)	*Scientific Studies of Reading*
Girouard-Hallam & Danovitch (2022)	*Developmental Psychology*
Gulz et al. (2020)	*International Journal of Artificial Intelligence in Education*
Hsiao et al. (2015)	*Interactive Learning Environments*
Justice et al. (2019)	*Journal of Learning Disabilities*
Kewalramani, Kidman et al. (2021)	*European Early Childhood Education Research Journal*
Kewalramani, Palaiologou et al. (2021)	*Australasian Journal of Early Childhood*
Kim et al. (2023)	*Journal of Autism and Developmental Disorders*
Su & Yang (2023)	*Interactive Learning Environments*
Xu, Aubele et al. (2022)	*Child Development*
Xu, Vigil et al. (2022)	*Journal of Applied Developmental Psychology*
Xu, Wang et al. (2021)	*Computers & Education*

8.3. The Publication Years of All Included Research Articles

As summarized in Table 5, although the intended timeframe for all pertinent research publications was set from 1955 to August 2023, all 18 included research articles were actually published between 2005 and 2023. Furthermore, while research studies on AI use in early childhood education began to emerge in 2005, it is only within the last four years that they have started to burgeon. Specifically, each of the previous years (2005, 2015, 2016, and 2019) produced only one research publication on the topic, while 2022 witnessed the highest number of publications (5), followed by 2020, 2021, and 2023, each with three publications. This analysis further cements that most of these articles (14) were actually published within the last four years.

Table 5. The included research articles (*N* = 18) related to the affordances of AI for use in early childhood education by year of publication.

Year of Publication from the Earliest to the Latest (Number of Publications)	**Author(s)**
2005 (1)	Addessi & Pachet
2015 (1)	Hsiao et al.
2016 (1)	Carpenter et al.
2019 (1)	Justice et al.
2020 (3)	(1) Aeschlimann et al. (2) Bonneton-Botté et al. (3) Gulz et al.
2021 (3)	(1) Kewalramani, Kidman et al. (2) Kewalramani, Palaiologou et al. (3) Xu, Wang et al.
2022 (5)	(1) de Castro Rodrigues et al. (2) de Haas et al. (3) Girouard-Hallam & Danovitch (4) Xu, Aubele et al. (5) Xu, Vigil et al.
2023 (3)	(1) Erbeli et al. (2) Kim, et al. (3) Su & Yang

8.4. The Countries of Study Origin

As summarized in Table 6, the number of countries involved in the research concerning the affordances of AI for use in early childhood education is not extensive. Specifically, the 18 included research articles came from 11 countries (10 from developed countries and one from the developing country of Brazil). The United States was the dominant contributor, with seven research articles, followed by Australia with two.

Table 6. The included research articles (N = 18) related to the affordances of AI for use in early childhood education from the 11 countries (by country from the most to the least).

Country (Number of Publications)	Author(s)
United States (7)	(1) Carpenter et al. (2016) (2) Erbeli et al. (2023) (3) Girouard-Hallam & Danovitch (2022) (4) Justice et al. (2019) (5) Xu, Aubele et al. (2022) (6) Xu, Vigil et al. (2022) (7) Xu, Wang et al. (2021)
Australia (2)	(1) Kewalramani, Kidman, & PalAIologou (2021) (2) Kewalramani, PalAIologou et al. (2021)
Sweden (1)	Gulz et al. (2020)
Brazil (1)	de Castro Rodrigues et al. (2022)
France (1)	Bonneton-Botté et al. (2020)
Italy (1)	Addessi & Pachet (2005)
South Korea (1)	Kim et al. (2023)
Taiwan (1)	Hsiao et al. (2015)
The Netherlands (1)	de Haas et al. (2022)
Hong Kong, China (Hong Kong is a special administrative region of the People's Republic of China) (1)	Su & Yang (2023)
Switzerland (1)	Aeschlimann et al. (2020)

RQ2: *What is the range of research studies that have been conducted on the affordances of AI for use in early childhood education?*
This question was addressed through numerical information on the study characteristics (study populations and study methods) as detailed in the following section.

8.5. The Range of Study Populations

As summarized in Table 7, the study populations ranged in age from 2 to 8 years. However, except for one study involving third graders (about 8 years old), all other studies centered predominantly on children ages 3-5 years, which fall within the preschool age range. Among the 18 research articles, there were 19 studies (with one article reporting on two studies), involving a total of 15,081 children across 11 countries.

Table 7. The included research articles (N = 18) related to the affordances of AI for use in early childhood education and their study populations.

Author(s) (Year of Publication)	Study Population
Addessi & Pachet (2005)	27 children (ages 3-5)
Aeschlimann et al. (2020)	72 children (ages 5-6)
Bonneton-Botté et al. (2020)	233 children (ages 5-6)
Carpenter et al. (2016)	1,224 children (ages 2-5): 307 in Study 1 and 917 in Study 2

Author(s) (Year of Publication)	Study Population
de Castro Rodrigues et al. (2022)	62 children (ages 3-4)
de Haas et al. (2022)	194 children (averaging 5 years and 8 months)
Erbeli et al. (2023)	12,171 third graders (presumably about age 8)
Girouard-Hallam & Danovitch (2022)	80 children: 40 children (ages 4-5) and 40 children (ages 7-8)
Gulz et al. (2020)	36 children (ages 4-6)
Hsiao et al. (2015)	57 children (ages 2-3)
Justice et al. (2019)	483 children (ages 3-5)
Kewalramani, Kidman et al. (2021)	21 children (ages 4-5)
Kewalramani, Palaiologou et al. (2021)	5 children (ages 4-7)
Kim et al. (2023)	106 children (ages 3-6)
Su & Yang (2023)	26 children (ages 3-5)
Xu, Aubele et al. (2022)	117 children (ages 37-81 months, averaging 58.10 months)
Xu, Vigil et al. (2022)	77 children (ages 4-6)
Xu, Wang et al. (2021)	90 children (ages 3-6)

8.6. The Range of Study Methods

As summarized in Table 8, the included studies encompassed four research methods (experimental, qualitative, quantitative, and intervention). However, more than half of the research articles (10 or 56%) employed an experimental design, followed by 3 quantitative-based, 2 qualitative-based, 2 intervention-based, and 1 involving both quantitative and qualitative designs.

Table 8. The included research articles (*N* = 18) related to the affordances of AI for use in early childhood education by study type.

Study Type	Author(s)
Experimental (10)	• Addessi & Pachet (2005) • Aeschlimann et al. (2020) • Bonneton-Botté et al. (2020) • de Castro Rodrigues et al. (2022) • de Haas et al. (2022) • Gulz et al. (2020) • Hsiao et al. (2015) • Xu, Aubele et al. (2022) • Xu, Vigil et al. (2022) • Xu, Wang et al. (2021)
Quantitative (e.g., measures, survey-type questions) (3)	• Erbeli et al. (2023) • Girouard-Hallam & Danovitch (2022) • Kim et al. (2023)
Qualitative (2)	• Kewalramani, Kidman, & PalAIologou (2021) • Kewalramani, PalAIologou et al. (2021)
Intervention (2)	• Justice et al. (2019) • Su & Yang (2023)
Both Quantitative and Qualitative (1)	Carpenter et al. (2016)

RQ3: *What is the nature of research studies that have been conducted on the affordances of AI for use in early childhood education?*

While the nature (e.g., study aim(s), method of data collection, main findings, main implications) of each research article was detailed earlier in Table 3a and Table 3b, thematic analysis further identified common themes emerging within and across all data. Specifically, four salient themes characterized the nature of the 18 included research articles (see Figure 2 and Table 9).

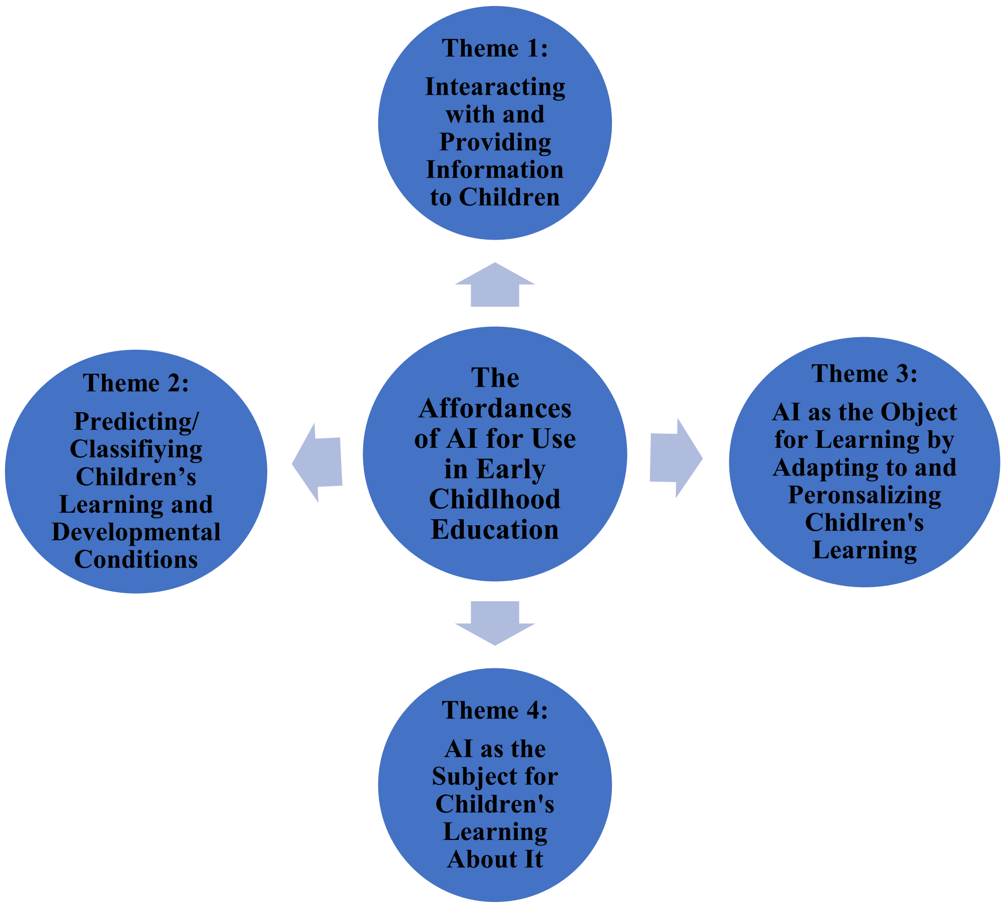

Figure 2. The four themes that characterized the affordances of AI for use in early childhood education.

Table 9. The themes and categories of the included research articles (N = 18) related to the affordances of AI for use in early childhood education.

Theme	Category	Benefits of AI
Theme 1: The affordances of AI tools for interactive learning and information retrieval: AI agents as interactive learning companions/support systems and informative virtual assistants	**AI as tangible tools:** (1) Peer-tutor robot for language learning and social interaction (de Haas et al., 2022) (2) Robot as a learning companion (Hsiao et al., 2015; Kewalramani, Kidman et al., 2021) (3) AI robotic toys as socially and emotionally supportive agents (Kewalramani, Palaiologou et al., 2021)	Advancing children's learning, development, and knowledge acquisition by providing support and assistance
	AI as intangible tools: (1) Voice assistants for social interaction (Aeschlimann et al., 2020) (2) Voice assistants for information retrieval (Girouard-Hallam & Danovitch, 2022) (3) Conversational agents (Xu, Aubele et al., 2022; Xu, Vigil et al., 2022; Xu, Wang et al., 2021)	Enhancing children's social interaction and language learning as well as assist in information retrieval
Theme 2: The affordances of AI technologies for predicting/classifying children's various mental, neurodevelopmental, and learning conditions	AI machine learning algorithm technologies as predictors/classifiers of children's risk for various mental, neurodevelopmental, or learning conditions: (1) anxiety disorders (Carpenter et al. (2016) (2) language disorder (Justice et al., 2019) (3) reading disabilities (Erbeli et al., 2023) (4) low-functioning autism spectrum disorder (Kim et al., 2022)	Assisting in predicting/classifying children's learning and development through machine learning algorithms
Theme 3: The affordances of AI as the object for learning by adapting to and personalizing children's learning	(1) An Interactive AI musical system (Addessi & Pachet, 2005) (2) AI-powered educational games (de Castro Rodrigues et al., 2022) (3) A digital handwriting notebook app (Bonneton-Botté et al., 2020)	Personalizing children's learning.
Theme 4: The affordances of AI as the subject for children's learning about it	(1) Children learn about AI by teaching an intelligent agent, through which they recognize that it is an entity with its own agency (Gulz et al., 2020) (2) AI literacy learning (through the use of AI technologies and tools in an AI curriculum) (Su & Yang, 2023)	Learning about AI.

8.7. Theme 1: AI as Tangible and Intangible Tools for Interactive Learning and Information Retrieval

As summarized in Table 9, AI serves various functions and purposes in early childhood education, notably as an interactive learning companion and as a mechanism for information retrieval. The role of AI tools as learning assistants is prominent in 50% of the 18 included research articles. These AI tools can be categorized into two groups: tangible and intangible. Tangible AI tools are found in peer-tutor robots for language learning and social interaction (de Haas et al., 2022), robots serving as learning companions (Hsiao et al., 2015; Kewalramani & Kidman, 2021), and robotic toys acting as socially and emotionally supportive agents (Kewalramani & Palaiologou, 2021). Intangible AI tools are found in conversational agents (Xu, Aubele et al., 2022; Xu, Vigil et al., 2022; Xu, Wang et al., 2021), as well as in voice assistants for social interaction (Aeschlimann et al., 2020) and information retrieval (Girouard-Hallam & Danovitch, 2022).

8.8. Theme 2: AI as Technologies for Predicting/Classifying Children's Conditions

As presented in Table 9, advanced AI technologies (e.g., machine learning algorithms, natural language processing) may be employed to predict or classify children's mental, learning, and neurodevelopmental conditions, as demonstrated in four of the included studies. Specifically, AI technologies are employed to predict children's risk for anxiety disorders (Carpenter et al., 2016), language disorder (Justice et al., 2019), reading disabilities (Erbeli et al., 2023), and low-functioning autism spectrum disorder (Kim et al., 2022).

8.9. Theme 3: AI as the Object for Learning

As summarized in Table 9, some AI technologies and tools can serve as the object for learning by adapting to children's learning and personalizing their learning experiences as demonstrated by the three included studies. Addessi and Pachet's (2005) study revealed how the use of AI-based interactive music systems enhanced children's music learning and musical creativity. Bonneton-Botté et al.'s (2020) study examined the benefits of using AI as a tool for analyzing the handwriting of children to provide real-time, personalized feedback concerning different aspects of their digital handwriting. These researchers found that only children with an initial medium writing level at the start of the study benefited from the digital application. de Castro Rodrigues et al.'s (2022) study demonstrated that the application of AI techniques to educational games was able to adjust to the user's needs in real time to help enhance children's literacy learning. The findings of all these studies suggest that the adaptive nature of AI is valuable in personalizing learning for children.

8.10. Theme 4: AI as the Subject for Learning

As summarized in Table 9, the findings of the two included studies (Gulz et al., 2020; Su & Yang, 2023) suggest that AI serves as the subject for children's learning about it. Gulz et al.'s (2020) study involved affording children the opportunity to teach an intelligent agent early math through a play-&-learn game. Through the eye-tracking data, Gulz et al. found that children gazed longer when the teachable agent was in control of gameplay than when it was not, demonstrating their understanding of the teachable agent as having its own agency. Su and Yang's (2023) study revealed that through an AI curriculum intervention, young children (ages 3-5) were able to acquire basic AI concepts and related knowledge, albeit there were developmental differences between the younger and older children. The findings of these two studies suggest that affording children the opportunity to learn about AI as the subject through various relevant activities can empower them to develop AI knowledge and literacy.

9. Discussion

Framed around Gibson's (1979) ecological theory highlighting the concept of *affordances*, I was able to map the global landscape on the affordances of AI for use in early childhood education based on the 18 research articles included in this scoping review, thereby revealing the current state of the knowledge in this area. Additionally, I was able to identify gaps in the knowledge base as opportunities for future research horizons. In this section, I first discuss the key findings vis-à-vis the three research questions on the extent, range, and nature of what these included articles conveyed, respectively. I then identify the three main research gaps and chart directions for future studies.

9.1. The Limited Extent of Studies on AI Use in Early Childhood Education

For this scoping study, the timeframe of research publications was set between 1955 (when the term *AI* was introduced) and 2023 (when the search of articles was conducted). Surprisingly, the finding reveals that all included research articles were actually published between 2005 and 2023. It suggests that although the concept of AI was introduced by McCarthy et al. (1955) nearly seven decades ago, empirical studies related to the affordances of AI for use in early childhood education only began to emerge in 2005, representing less than two decades of research in the area. A further surprise is that the majority (14 out of 18) of the included research articles were published within the last four years, between 2020 and 2023. These findings suggest that research on AI use for children is still in its nascent stage, with efforts to chart this territory intensifying only in recent years.

My scoping review shows that, at this stage in the research, the relatively small body of 18 included articles primarily came from developed countries (10), with only one from a developing country. This finding is not surprising, as developed countries tend to have more resources to invest in AI infrastructure to promote societal progress and economic growth. It also suggests that the affordances of AI for use in early childhood education have not achieved global prevalence. That is, although AI technologies and tools are increasingly proliferating, they seem to be concentrated in only a small number of countries. Notably, the United States was the biggest contributor, with seven research publications on the topic of interest. However, this body of seven research articles still seems scant, even in this country, especially considering the span of nearly two decades. Nonetheless, the United States may be regarded as more technologically advanced than other countries, as it has contributed some notable AI innovations, such as Chat Generative Pre-trained Transformer (ChatGPT) launched in November 2022 and Generative Pre-trained Transformer-4 Omni (GPT-4o) (a large language model with multimodal, multilingual capacities) released in May 2024, all by OpenAI, as well as voice/virtual assistants (e.g., Apple's Siri, Amazon's Alexa, Google Assistant). In sum, it is conceivable that AI technologies and tools are predominantly invented and deployed in economically advanced nations. Consequently, their direct applicability to developing countries with emerging economies might be limited due to the absence of a conducive AI infrastructure needed to fully harness the potential of these advanced technologies for educational purposes. Furthermore, the overall paucity of research articles on AI use in early childhood education globally over the last two decades suggests an imperative need for more empirical efforts in this area to provide better informed insights.

The finding that the United States was the dominant force in contributing research insights on AI affordances in early childhood education may have another possible explanation. It may be because more researchers or groups of researchers in the United States were interested in studying the topic of AI use in early childhood education and subsequently published their related findings in peer-reviewed academic journals more than researchers elsewhere. This finding might motivate researchers everywhere to study this topic more, thereby yielding a more comprehensive understanding of the affordances of AI for use in early childhood education at scale.

9.2. The Range of Studies on AI Use in Early Childhood Education

This scoping review reveals that the range of the 18 included research articles covered 15,081 children (ages 2 to 8) across 11 countries. However, most of these studies (e.g., Addessi & Pachet, 2005; de Castro Rodrigues et al., 2022; Girouard-Hallam & Danovitch, 2022; Justice et al., 2019; Kewalramani, Kidman et al., 2021; Su & Yang, 2023) focused on preschool children (ages 3-5). This finding is understandable, especially considering that this age range is globally accepted as early childhood years (e.g., in the United States, NAEYC, 2022; in China, Li & Chen, 2023). Furthermore, these early childhood years are considered a critical period marked by rapid development and learning for children, laying the foundation for their later development (Shonkoff & Phillips, 2000). Thus, this developmental period may be considered the optimal time to offer young children an AI education and curriculum focused on learning about AI and using AI tools for learning. This type of educational intervention has been shown to benefit preschool children's acquisition of AI knowledge and literacy (e.g., Gulz et al., 2020; Su & Yang, 2023).

This scoping review also reveals that although various research methods were employed, most of the included studies (Addessi & Pachet, 2005; Aeschlimann et al., 2020; Bonneton-Botté et al., 2020; de Castro Rodrigues et al., 2022; de Haas et al., 2022; Gulz et al., 2020; Hsiao et al., 2015; Xu, Aubele et al., 2022; Xu, Vigil et al., 2022; Xu, Wang et al., 2021) were experimental in design. This finding is not surprising, especially given that many emerging AI technologies and tools may not yet have been tested for proof of concept. In this case, an experimental design would be an ideal approach for testing new concepts, such as comparing specific learning between children in the AI condition and those in other conditions.

9.3. The Nature of the Research Studies on AI Use in Early Childhood Education

Adopting Gibson's (1979) concept of affordances for the purpose of this scoping study, I uncovered that various AI affordances have made children direct or indirect beneficiaries. Specifically, thematic analysis revealed four areas of affordances of AI for use with, by, and for children.

First, the included research articles conveyed two types of affordances of technology-embedded and user-friendly AI-interfaced tools: tangible (e.g., robots, robotic toys) (e.g., Hsiao et al., 2015; Kewalramani, Kidman et al., 2021) and intangible (e.g., voice assistants, conversational agents) (e.g., Aeschlimann et al., 2020; Girouard-Hallam & Danovitch, 2022; Xu, Aubele et al., 2022; Xu, Vigil et al., 2022; Xu, Wang et al., 2021). The findings of these studies suggest that different types of AI tools can afford different opportunities for children to engage with AI in specific ways to achieve specific outcomes for specific purposes. In addition to the classic sociocultural theory, which posits that children learn best through social interactions with other humans (Vygotsky, 1978), the findings regarding the functions of these two types of AI introduce a more contemporary approach to learning. This newer approach involves interactions and engagement with non-humans (i.e., AI agents) as learning companions and social partners.

Second, AI machine learning algorithms can be applied to predict children's risk for various mental, neurodevelopmental, and learning conditions. The four included research studies (Carpenter et al., 2016; Erbeli et al., 2023; Justice et al., 2019; Kim et al., 2022) reveal that AI technologies have been instrumental in predicting/classifying children's mental, neurodevelopmental, and learning conditions. The finding of this particular type of AI affordance is not surprising, especially considering that machine learning technologies and techniques can enable intelligent systems to learn patterns, adapt to data, and make predictions to help inform early intervention efforts. In this case, AI can indirectly benefit children's learning and development through its ability to predict or classify their various conditions, if any. This finding has implications for the use of AI for potentially diagnosing children's conditions, which may provide useful insights to guide early interventions for diagnosed children, thereby better supporting their learning.

Third, AI systems can serve as the object for learning by integrating algorithms and data-informed techniques to adapt to individual children's learning and use the data to make informed decisions regarding personalized learning for them (Addessi & Pachet, 2005; Bonneton-Botté et al., 2020; de Castro Rodrigues et al., 2022). Due to their adaptive nature, these AI-driven systems and platforms are equipped with the ability to construct personalized experiences for children (Crescenzi-Lanna, 2023). Furthermore, while AI tools can benefit all children, they can also help create a level playing field, especially for those who need personalized support the most.

Fourth, it is one thing to afford AI technologies and tools to children for educational purposes, it is quite another to equip them with AI knowledge by leveraging AI as the subject for learning. This scoping study reveals that some AI systems and tools can serve as the subject for children's learning about AI. Specifically, two included studies (Gulz et al., 2020; Su & Yang, 2023) demonstrated that children could acquire knowledge about AI through direct interaction with a teachable intelligent agent and/or engagement with an intentional AI curriculum. This finding suggests that AI curricula and activities are valuable affordances for children to learn about the nature of AI, including its design, functions, use, and agentic capabilities.

While the thematic evidence suggests that the aforementioned four areas of affordances of AI for use in early childhood education are distinct enough to be independent, it is worth noting that they are not necessarily mutually exclusive. For example, Theme 1 highlights AI as interactive learning tools, which may overlap with Theme 2, focusing on AI as adaptive learning tools capable of personalizing learning. Furthermore, the four thematic findings also support Abbass's (2021) idea that AI are "social and cognitive phenomena" (p. 94). For instance, as demonstrated by some of the included studies (e.g., Aeschlimann et al., 2020, de Haas et al., 2022; Hsiao et al., 2015; Kewalramani, Kidman et al., 2021; Kewalramani, Palaiologou et al., 2021; Xu, Aubele et al., 2022; Xu, Vigil et al., 2022; Xu, Wang et al., 2021), AI can interact with children as social partners and also support their cognitive development by serving as tutors and personalizers of learning.

9.4. Research Gaps and Directions for AI Use in Early Childhood Education

This scoping review of the 18 included empirical studies reveals the affordances of AI for early childhood education. It also identifies three main research lacunas, thereby charting directions for future studies in three corresponding areas: (1) interviewing and/or surveying education stakeholders (parents, educators, policymakers) regarding the affordances of appropriate AI for use with, by, and for children within the context of ethical considerations; (2) conducting group comparisons of contextual constraints contributing to the "AI divide" among children from different socioeconomic backgrounds; and (3) comparing sociocultural influences on AI use in early childhood education across cultures.

The first research gap concerns the consideration of ethical factors. The included research studies demonstrate that various AI technologies and tools have been utilized, whether to facilitate and adapt to children's learning or to predict and classify children's conditions for potential early intervention. However, none has examined what I characterize as the *appropriate development, deployment, and employment of AI in early childhood education*. I emphasize appropriateness here to refer to a wide range of ethical considerations (e.g., responsibility, safety, privacy) that scholars have previously discussed (e.g., Chen & Lin, 2024; Javed et al., 2022; Kurian, 2023, 2024; McStay & Rosner, 2021; Zhang et al., 2021).

As AI has increasingly become a global phenomenon, legitimate concerns have also arisen regarding the ethical development, deployment, and use of innovative AI technologies and tools. As reported by OECD in 2021, globally, there have been over 1,000 AI ethical policies initiated by 69 countries, territories, and the European Union. More specifically, Jobin et al. (2019) conducted a scoping review of available guidelines on ethical AI to map the global landscape in this area. In identifying and analyzing the 84 documents issued by various organizations, including private companies, governmental agencies, academic and research institutions, and professional associations/scientific societies, Jobin et al. uncovered a global convergence around five ethical principles: "transparency," "justice and fairness," "non-maleficence," "responsibility," and "privacy." Even more specifically, in the context of education, Adams et al. (2023) conducted a content analysis of the most globally applicable documents informing AI ethics policy and practice in K-12 education issued by four global organizations: World Economic Forum (2019), IEAIED (2021), UNESCO (2021), and UNICEF (2021). Adams et al. identified, in addition to the core principles that Jobin et al. (2019) already reported, four more ethical principles specific to K-12 education, namely "Pedagogical appropriateness; Children's rights; AI literacy; and Teacher well-being" (p. 4).

Recognizing that the use of AI is a "double-edged sword" that comes with both educational benefits and ethical challenges, Chen and Lin (2024) advocated the need for education stakeholders, especially teachers, parents, and children, to develop and apply critical AI literacy. Specifically, Chen and Lin propounded the POWER (an acronym which stands for Purposeful, Optimal, Wise, Ethical, Responsible) principles to guide the appropriate use of AI for educational purposes. However, the POWER theoretical framework has not been empirically tested. Future research might consider testing this framework. For instance, one might investigate this overarching research question: *How can AI be used in purposeful, optimal, wise, ethical, and responsible ways to benefit children's learning and development in early childhood education?*

While a variety of AI ethical guidelines have been formulated and articulated worldwide, researchers have also begun examining ethical issues specific to certain AI technologies and tools. For instance, it has been recognized that AI conversational agents may pose potential dangers due to what Kurian (2023, 2024) termed the "empathy gap," which refers to the discrepancy between AI systems and tools designed to mimic human-like empathy (e.g., intentions, emotions) and their lack of genuine empathy. The latter can lead to inappropriate responses or suggestions from conversational AI systems, potentially jeopardizing a child's well-being, even for those beyond the early childhood years. For instance, when a 10-year-old girl asked for a "challenge to do," Amazon's Alexa suggested an unsafe activity of touching a penny to an active plug, which could result in electric shock or even cause a fire (BBC News, 2021). Cautioned by incidents of inappropriate or risky suggestions from AI conversational agents, Kurian (2024) advocated for safeguarding children and their well-being by establishing guardrails for the child-safe design and deployment of AI. Specifically, Kurian recommended that stakeholders (e.g., policymakers, AI developers, educators, parents) consider eight dimensions in AI design and policy: "content and communication; human intervention; transparency; accountability; justifiability; regulation; school-family engagement; and child-centred design methodologies" (p. 1).

The AI ethical policies, guidelines, and principles established by global and national organizations as well as educational researchers have heightened awareness of ethical issues associated with AI use, while providing theoretical guidance. Yet, the concrete applications of these AI policies, guidelines, and principles bearing ethical considerations in early childhood education have not been researched, as revealed by this scoping review. Given this research gap, future studies could interview and/or survey education stakeholders (especially parents, teachers, and policymakers) to investigate whether they are implementing any AI ethical policies, which policies they are implementing, and how. Relatedly, these studies might address research questions such as:

- Do early childhood educational settings implement ethical policies/guidelines for AI use with, by, and for children? If so, what are they, and how do they implement them?
- If, and how do different countries and/or regions address ethical challenges and implement ethical policies/guidelines surrounding the use of AI in early childhood education?
- Are stakeholders (e.g., children, parents, educators, policymakers) trained about ethical issues surrounding the use of AI in early childhood education? If so, how? If not, why not?

The second research gap concerns the influence of contextual factors. This scoping study reveals that research has explored how AI has been utilized in early childhood education to contribute to various educational benefits for children. However, there are contextual constraints that can bar some other children from reaping such benefits. It has been documented that a "digital divide" exists between the rich and the poor, or between those with access to the Internet and other digital opportunities and those without (Blackwell et al., 2014). Similarly, there is also an "AI divide" between children with affordances of AI technologies and tools to benefit their learning and those without (Huang et al., 2021). In this case, similar to the digital divide, the AI divide raises concerns about social inequities for children who do not have access to AI technologies as others, thereby hindering AI transformation in early childhood education at scale. To mitigate AI-related inequities, it is crucial that educational policies prioritize investment in an effective AI infrastructure and establish developmentally appropriate AI resources and tools for learning that are accessible to all children, especially those who need them the most. In light of these implications and considerations, future research might conduct group comparisons to identify contextual constraints related to the AI divide, particularly the inequitable affordances of AI tools among children from various socioeconomic backgrounds by exploring questions such as:

- Do socioeconomically diverse early childhood educational settings differ in the affordances of AI tools for children, and if so, how?
- If, and how do the inequitable affordances of AI tools for children from different socioeconomic backgrounds affect their learning outcomes?
- How can early childhood educational settings address issues of diversity, equity, inclusion, and access when implementing AI for children?

The third research lacuna concerns the influence of cultural factors. This scoping review found no studies that have examined potential cultural differences in AI use within and across early childhood education. Future research addressing this gap could uncover cultural affordances and constraints that may either spur or bar children's ability to leverage AI to enhance their learning. Previous research has demonstrated that culturally specific beliefs about child development and learning can influence parenting and pedagogical practices, which, in turn, affect children's learning experiences and developmental outcomes across different cultures (e.g., Chen, Li et al., 2017; Chen & Liang, 2017; Chen et al., 2024; Chen, Sun et al., 2017). In this context, different cultural beliefs may lead to varying degrees and types of AI integration in early childhood educational settings across cultures. By identifying and contextualizing these cultural factors, we can develop a more nuanced, culturally specific perspective and provide contextual implications to inform the global applicability of AI in early childhood education. We can do so by conducting cross-cultural studies that compare sociocultural affordances of AI use, exploring questions such as:

- How do stakeholders (e.g., parents, educators, policymakers) in different cultures perceive the affordances of AI for use with, by, and for children?

- What AI tools do stakeholders in different cultures provide for children, and how are they implemented?
- How do children from different cultures engage with the AI tools afforded to them?

Taken together, while this scoping study has addressed the *what* (AI technologies and tools) and the *why* (purposes) aspects of AI affordances in early childhood education, other research questions remain unexplored. Specifically, the aforementioned research gaps foreground the need to investigate the *where* (cultural considerations), the *how* (ethical considerations), and the *for whom* (equitable considerations) to contextualize the various affordances of AI tools for children. Addressing these gaps will provide valuable insights to inform both practice and policy in early childhood education.

10. Study Limitations

This scoping study contributes new insights into the extent, range, and nature of the affordances of AI for use in early childhood education. However, it has limitations. One limitation concerns the inclusion and exclusion of research articles. Specifically, since this review only included those studies published in refereed journals as a common standard of quality control in the fields of education and psychology, those from the gray literature (e.g., dissertations, conference proceedings, reports) were excluded. In Su and Yang's (2022) scoping review of AI in early childhood education, 12 out of 17 included publications were conference proceedings. Thus, it is possible that there may be eligible research articles in gray literature that could provide additional or complementary findings to this review. However, as mentioned earlier, some of the conference proceedings included in Su and Yang's scoping review were not research articles.

Another limitation concerns the searchability of articles. In some countries, research articles may be indexed in national or local databases using keywords available only in local languages. Thus, it is possible that such research articles might have been missed. Nonetheless, future research might consider including databases other than the three prominent ones used in this scoping study. This inclusion might yield additional search results.

11. Conclusion

In recent years, AI innovations have progressively transformed our daily functions. In early childhood education, some children have been afforded the opportunity to teach, trust, rely on, learn from, and interact with a variety of AI tools. Given the rapid evolution of AI, it is expected that more advanced AI tools will emerge, offering broader applications for both teachers and young learners. For example, more effective and efficient AI tools and applications may be developed and deployed in early childhood education, further enhancing teaching and learning.

As scientists and developers continue to invent new AI technologies, systems, tools, and applications, researchers should also keep pace by collating and codifying empirical knowledge about their use. This scoping study represents such an effort by synthesizing the current state of knowledge, which highlights the affordances of AI for use in early childhood education. However, it appears that we are currently in a liminal state, in between leveraging AI sporadically and integrating it more fully to benefit children's learning. Thus, I agree with Crescenzi-Lanna (2023) that "artificial intelligence will become a revolutionary tool to support learning and teaching processes, but today we can only glimpse, in embryonic form, these potentialities in its applications" (p. 30). Reflecting the nascent stage of AI deployment and employment in supporting children's learning and development, the findings of this scoping review make evident that much remains to be discovered, underscoring the need for further research, particularly in the three aforementioned areas, to continue cultivating this field of study.

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*denotes that the research article was included in this scoping study.