Journal of Computers in Education (2025) 12(1):93–131
https://doi.org/10.1007/s40692-023-00304-9

Artificial intelligence (AI) learning tools in K-12 education: A scoping review

Iris Heung Yue Yim[1] · Jiahong Su[2]

Received: 15 July 2023 / Revised: 4 October 2023 / Accepted: 25 October 2023 /
Published online: 6 January 2024

Abstract
Artificial intelligence (AI) literacy is a global strategic objective in education. However, little is known about how AI should be taught. In this paper, 46 studies in academic conferences and journals are reviewed to investigate pedagogical strategies, learning tools, assessment methods in AI literacy education in K-12 contexts, and students' learning outcomes. The investigation reveals that the promotion of AI literacy education has seen significant progress in the past two decades. This highlights that intelligent agents, including Google's Teachable Machine, Learning ML, and Machine Learning for Kids, are age-appropriate tools for AI literacy education in K-12 contexts. Kindergarten students can benefit from learning tools such as PopBots, while software devices, such as Scratch and Python, which help to develop the computational thinking of AI algorithms, can be introduced to both primary and secondary schools. The research shows that project-based, human–computer collaborative learning and play- and game-based approaches, with constructivist methodologies, have been applied frequently in AI literacy education. Cognitive, affective, and behavioral learning outcomes, course satisfaction and soft skills acquisition have been reported. The paper informs educators of appropriate learning tools, pedagogical strategies, assessment methodologies in AI literacy education, and students' learning outcomes. Research implications and future research directions within the K-12 context are also discussed.

Keywords Artificial intelligence literacy · K-12 students · AI literacy education · Learning tools · Review

✉ Iris Heung Yue Yim
hyy25@cam.ac.uk

Jiahong Su
maggiesu@connect.hku.hk

1 Faculty of Education, University of Cambridge, 184 Hills Road, Cambridge CB2 8PQ, UK

2 Faculty of Education, The University of Hong Kong, Pok Fu Lam, Hong Kong SAR, China

Introduction

Artificial intelligence (AI) was defined in 1956 as "the science and engineering of creating intelligent machines" (McCarthy, 2004, p.2). AI education is considered a driver of economic growth, future workforce development, and global competitiveness (Cetindamar et al., 2022; Sestino & De Mauro, 2022). Researchers' interest in equipping students with AI knowledge, skills, and attitudes to thrive in an AI-rich future (Miao et al., 2021; Rina et al., 2022; Wang & Cheng, 2021) has given rise to the term "AI literacy", which concerns the design and implementation of AI learning activities, learning tools and applications, and pedagogical models. Some educators focus on demonstrating machine learning through activities for mastering coding skills and AI concepts (Marques et al., 2020), while others suggest focusing on computational thinking and engagement in deductive and logical reasoning practices (Wong, 2020). In this paper, it is argued that AI education should be extended beyond universities to K-12 students.

There have been a number of recent studies of AI in the context of kindergartens (Su & Yang, 2022; Williams et al., 2019a, 2019b), primary schools (Ali et al., 2019; Shamir & Levin, 2021), and secondary schools (Norouzi et al., 2020; Yoder et al., 2020). However, little is known about what and how AI should be taught (Su et al., 2023a; Ng et al., 2023; Van Brummelen et al., 2021). One challenge is delivering AI content in an age-appropriate and effective manner (Su et al., 2023b; Su & Yang, 2023). Despite the numerous AI learning tools available in K-12 contexts (Rizvi et al., 2023; Van Brummelen et al., 2021), such as Turtle Robot (Papert & Solomon, 1971), PopBots (Williams et al., 2019a) and LearningML applications (Rodríguez-García et al., 2020), many educators are concerned about the suitability of these tools (Chiu & Chai, 2020; Su & Yang, 2023).

With the development of age-appropriate learning tools, AI concepts can be simplified via visual representation, such as block-based programming (Estevez et al., 2019). For example, Scratch, a high-level block-based programming language, allows students with limited reading ability to create computer programs by using illustrations and visual elements (such as icons and shapes) without having to rely on traditional written instructions (Park & Shin, 2021). AI tools and platforms, including Zhorai (Lin et al., 2020), Learning ML (Rodríguez-Garciá et al., 2021), Machine Learning for Kids (Sabuncuoglu, 2020), and Scratch (Li & Song, 2019), have a positive impact on students' AI knowledge and skills. Chen et al. (2020) noted that despite the introduction of various learning tools to teach AI, there has not been enough discussion on how AI content should be taught and how tools should be used to support pedagogical strategies and related educational outcomes.

Theoretical model

The technology-based learning model of Hsu et al. (2012) is adopted and modified in this study; it has been widely used by other researchers conducting similar systematic reviews (Chang et al., 2018, 2022; Darmawansah et al., 2023; Tu & Hwang, 2020), as shown in Fig. 1. Hsu et al. (2012) suggested cross-analyzing academic research trends by examining the associations among three categories: research methods, research issues, and application domains. They argue, for example, that by exploring how the topic of a study may affect the selection of its sample and participants, a more thorough and comprehensive analysis can be conducted. Their proposed technology-based learning model has helped frame the research questions of the present study.

According to Hsu et al. (2012), "research methods", "research issues", and "application domains" are the three main categories to be considered in the development of a coding scheme to gauge research trends in the field of technology-based learning and education. In terms of research methods, a quantitative, qualitative, and mixed approach is employed in this study to construct the coding scheme for

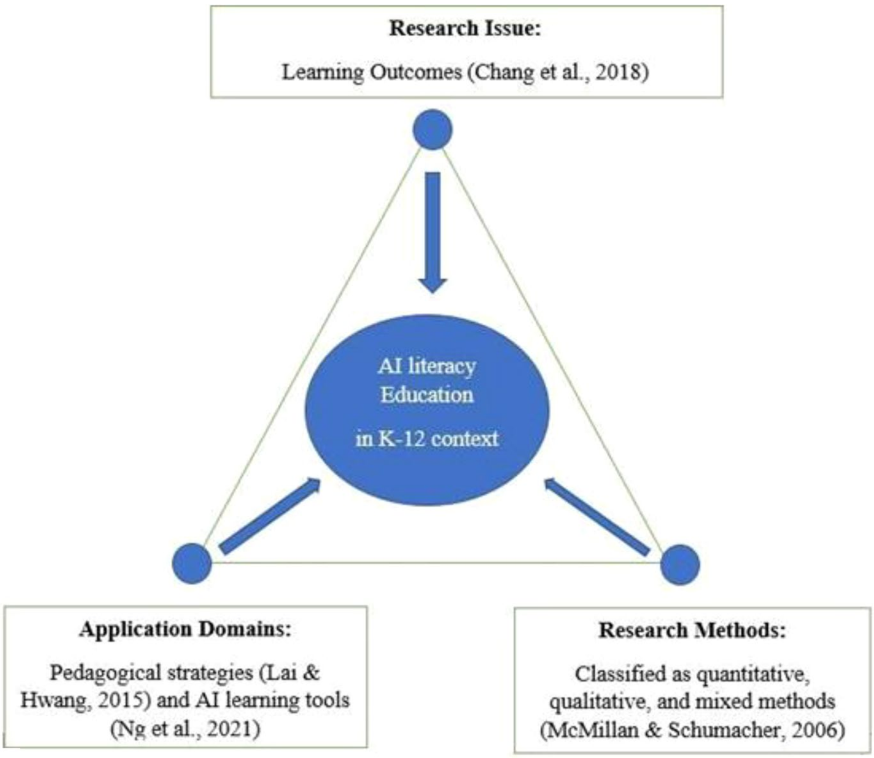

Fig. 1 Modified technology-based learning model by the researchers of this review (adopted from Hsu et al., 2012)

the review of the literature (McMillan & Schumacher, 2010). In terms of research issues, with reference to Chang et al. (2018), learning outcomes are categorized as cognitive, affective, behavioral, and skills acquisition outcomes. Finally, two application domains are pursued in this paper: (1) the pedagogical strategies commonly used in science courses, which were employed by Lai and Hwang (2015) and which include constructive, reflective, didactic, and unplugged pedagogies (Cope & Kalantzis, 2016), and (2) the learning tools, namely, hardware, software, intelligent agents, and unplugged strategies, which are coded as suggested by Ng and Chu (2021).

Research objectives

In this study, the literature on pedagogical strategies, assessment methods, learning tools, and learning outcomes in AI K-12 settings is studied. Four research questions are formulated.

- RQ1: What are the potential learning tools identified in AI K-12 education?
- RQ2: What pedagogical strategies are commonly proposed by studies on AI K-12 learning tools?
- RQ3: What learning outcomes have been demonstrated in studies on AI K-12 learning tools?
- RQ4: What are the research and assessment methods used in studies on AI K-12 learning tools?

Methods

This study follows the same four steps employed in other studies on AI literacy in K-12 (e.g., Ng et al., 2022; Su et al., 2022): (1) identifying relevant studies, (2) selecting and excluding eligible studies, (3) data analysis, and (4) reporting findings. In this study, the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines (Moher et al., 2015) are followed.

Identifying relevant studies

The electronic databases used for the literature search were ACM, EBSCO, Web of Science, and Scopus. The aim of this review is to provide a comprehensive K-12 education for learning tools, encompassing early childhood education and primary and secondary education. As the education systems of different countries may differ from each other, the search string used in the paper for K-12 includes from kindergarten to secondary school students. In addition, learning tools are defined as a variety of learning platforms and systems, educational applications and activities that can enhance the teaching process and support students in AI literacy learning.

Table 1 Search string

Databases	Search string
ACM	[[Title: "artificial intelligence"] OR [Title: "ai"] OR [Title: "ai literacy"] OR [Title: "artificial intelligence literacy"] OR [Title: "machine learning"] OR [Title: "ml"]] AND [[Title: "primary school*"] OR [Title: "preschool*"] OR [Title: "kindergarten*"] OR [Title: "pre-k*"] OR [Title: "secondary school*"] OR [Title: "high school*"] OR [Title: "k-12"]]
EBSCO	TI ("Artificial Intelligence" OR "AI" OR "AI literacy" OR "Artificial Intelligence literacy" OR "Machine learning" OR "ML") AND TI ("primary school*" OR "preschool*" OR "kindergarten*" OR "pre-k*" OR "secondary school*" OR "high school*" OR "K-12") AND TI ("learning" OR "learning tools" OR "learning systems")
Web of Science	"Artificial Intelligence" OR "AI" OR "AI literacy" OR "Artificial Intelligence literacy" OR "Machine learning" OR "ML" (Title) AND "primary school*" OR "preschool*" OR "kindergarten*" OR "pre-k*" OR "secondary school*" OR "high school*" OR "K-12" (Title) AND "learning" OR "learning tools" OR "learning systems" (Title)
Scopus	AT ("Artificial Intelligence" OR "AI" OR "AI literacy" OR "Artificial Intelligence literacy" OR "Machine learning" OR "ML") AND AT ("primary school*" OR "preschool*" OR "kindergarten*" OR "pre-k*" OR "secondary school*" OR "high school*" OR "K-12") AND AT("learning" OR "learning tools" OR "learning systems")

Therefore, the search strings are reflected with specific definitions for K-12 and learning tools to search for target articles and data, as shown in Table 1.

Study selection and exclusion

To ensure the generalizability of the findings and to avoid biases in article selection, specific inclusion and exclusion criteria are employed in this study (Table 2).

As shown in Fig. 2, a total of 326 articles were identified, 105 from EBSCO, 81 from Web of Science, 110 from Scopus, and 30 from ACM. The exclusion criteria were as follows: (1) studies that were irrelevant to the research topic (N = 251). For example, Bai and Yang (2019) were excluded since the research applied a deep learning technology recommendation system to improve teachers' information technology ability. It was conducted in contexts other than those of AI literacy education, learning and instruction. Mahon et al. (2022) presented the design of an online machine learning and artificial intelligence course for secondary school students; however, they did not discuss in detail what type of learning tools can be used and how to support students' AI literacy learning. A discussion paper by Karalekas et al. (2023), a theoretical paper by Leitner et al. (2023) and a scoping review by Marques et al. (2020) were also removed because they were not empirical studies, and they did not involve conducting any practical experiment. (2) Duplicate studies (N = 10), (3) studies that were not written in English (N = 4), (4) non research studies (N = 10), and other types of articles (N = 8). Finally, 46 studies were selected, as shown in Appendix 1.

Table 2 Article selection—inclusion and exclusion criteria

	Inclusion criteria	Exclusion criteria
Language	Written in English	Languages other than English
publication type	Peer reviewed studies are included, such as conference proceedings and research papers published in the journals indexed by the aforementioned databases	Editorials, magazines, books, book chapters, dissertations, discussion and conceptual papers are excluded
Measure	Studies related to AI literacy education, such as those that discuss learning tools, pedagogical strategies, learning outcomes, and assessment methods	The focus is not related to AI literacy education. Courses or activities are not related to AI concepts, machine learning, or subset
Content	Studies should respond to one or more of the terms related to the topics of the RQs	The focus is solely on AI technologies in education and not related to AI literacy education
Population	K-12 settings or within the age range of K-12 schools	Higher and adult education are excluded

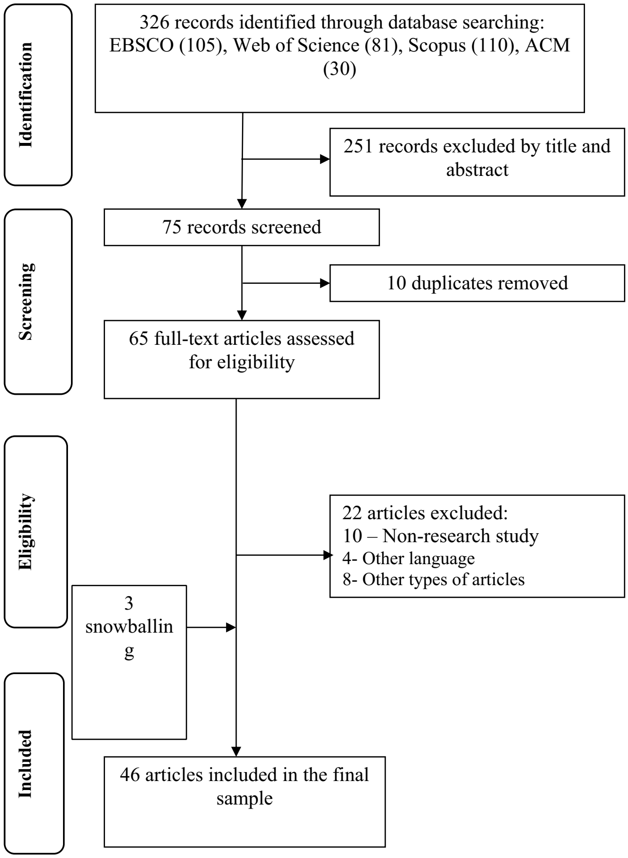

Fig. 2 PRISMA diagram of included articles in the scoping review

The snowball method

To enhance the systematic search for relevant literature, the snowballing method as outlined by Sayers (2008) was employed. This involved tracing references in previously selected articles. The focus was on the references cited in the earlier selected articles as discovered through Google Scholar. Utilizing the snowballing method led to the identification of three additional articles that met the eligibility criteria described above.

Overview of selected studies

Table 3 presents an overview of the 46 selected studies, including the type of articles, year of publication, and educational level.

Table 3 The characteristics of the reviewed articles

Variables	Categories	N	%
Types of articles	Conference papers	28	60.87
	Journal articles	18	39.13
Year	1995	1	2.17
	2010	1	2.17
	2012	1	2.17
	2018	4	8.70
	2019	7	15.22
	2020	10	21.74
	2021	14	30.44
	2022	4	8.70
	2023 (up to Sept)	4	8.70
Countries	Australia	2	4.34
	Brazil	1	2.17
	China	7	15.22
	Denmark	1	2.17
	Finland	3	6.52
	Greece	1	2.17
	Hong Kong	3	6.52
	Indonesia	1	2.17
	Israel	3	6.52
	Japan	2	4.35
	New Zealand	1	2.17
	Norway	1	2.17
	Spain	3	6.52
	Sweden	1	2.17
	Thailand	1	2.17
	UK	1	2.17
	USA	8	17.39
	Do not mention	6	13.07
Educational level	Kindergarten	5	10.87
	Primary School	20	43.48
	Secondary School	20	43.48
	Across K-12	1	2.17

Publication trends

Forty-six articles were identified: 28 conference papers and 18 journal articles. The first article was published in 1995, and 39 articles have been published in the past 5 years, with a peak in 2021 (Fig. 3).

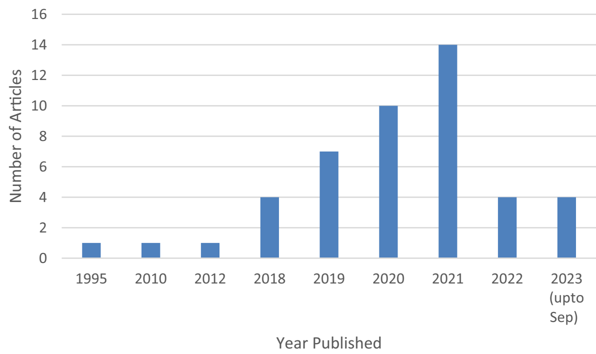

Fig. 3 The trend of AI literacy education in K-12 contexts

Countries

Most research took place in the USA (N = 8), China (N = 7), Finland (N = 3), Hong Kong (N = 3), Israel (N = 3), Spain (N = 3), Australia (N = 2) and Japan (N=2). Others were conducted in Brazil, Denmark, Greece, Indonesia, New Zealand, Norway, Sweden, Thailand, and the UK. The locations of the remaining six articles are unknown.

Educational levels

Primary and secondary schools are both the most researched educational levels, each covering 44% of the selected articles, followed by kindergartens (11%) and K-12 education (2%).

These selected studies generally include samples of students of both genders and a wide range of ages, from 3-year-old kindergarten students (Vartiainen et al., 2020) to 20-year-old Danish high school students (Kaspersen et al., 2021). It also encompasses participants in science technology engineering mathematics (STEM) classes (Ho et al., 2019), high-performing students of the Scientists in School program (Heinze et al., 2010), students with and without an AI background (Yoder et al., 2020), and students from varying socioeconomic backgrounds (Kaspersen et al., 2021).

There were three AI-related research studies between 1995 and 2017, mostly adopting unplugged activities and games for AI teaching, which are different from research conducted after 2017. The first article was published by Scherz and Haberman (1995), who designed a special AI curriculum with the use of abstract data types and instructional models (e.g., graphs and decision trees) to teach AI concepts such as logic programming and AI systems to high school students in Israel. In another two studies, the use of programming robots (Heinze et al., 2010) and computer science unplugged activities (Lucas, 2009) were explored with Australian and New Zealand K-6 students, respectively. Since then, a greater variety of learning tools have been employed and expanded to European and Asian countries across all educational levels in K-12 settings. Appendix 1 provides an overview of the selected articles.

Findings

RQ1: What are the potential learning tools identified in AI K-12 education?

The potential learning tools identified in K-12 contexts were intelligent agents (N = 20), software-focused devices (N = 19), hardware-focused devices (N = 10), and unplugged activities (N = 6) (Fig. 4 and Table 4). In this section, intelligent agents, software devices, and hardware devices are discussed.

Intelligent agents

Intelligent agents, such as Google Teachable Machine, Learning ML, and Machine Learning for Kids, which make decisions based on environmental inputs by using their sensors and actuators, are the most popular learning tools for enhancing students' computational thinking skills within K-12 contexts. Teachable Machine is a web-based tool developed by Google and is found to be more effective than are unplugged activities in kindergarten settings (Lucas, 2009; Vartiainen et al., 2020). In Vartiainen et al. (2020), children aged between 3 and 9 autonomously explored the input─output relationship with Google Teachable Machine, which fostered their intellectual curiosity, developed their computational thinking, and enhanced their understanding of machine learning. In both primary (Toivonen et al., 2020; Melsión et al., 2021) and secondary schools (Kilhoffer et al., 2023; Martins et al., 2023), Google Teachable Machine has been employed, allowing students to use their webcams, images, or sounds without coding to develop their own machine learning classification models.

In addition, Learning ML has been employed for primary schools to create AI-driven solutions and models, for example, to teach the supervised machine learning principle (Voulgari et al., 2021; Rodríguez-Garciá et al., 2021), which simplifies abstract AI algorithms for primary school students. Machine Learning for Kids,

Fig. 4 Summary of learning tools used in AI K-12 education

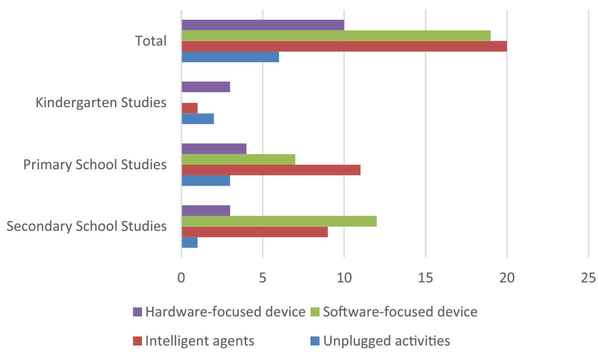

Table 4 AI learning tools adopted in K-12 educational setting

	Definition	Learning artefacts	Kindergarten (Sample studies)	Primary school (Sample studies)	Secondary school (Sample studies)
Intelligent agents (N = 20)	Use autonomous entities to make decisions based on environmental inputs using their sensors and actuators	Google's Teachable Machine, Learning ML, ecraft2learn, Votes-tratesML, Cognimates, Machine Learning for Kids, SmileyCluster	Vartiainen et al. (2020)	Rodríguez-Garciá et al. (2021) Shamir and Levin (2021); Toivonen et al. (2020)	Fernández-Martínez et al. (2021); Kilhoffer et al. (2023); Martins et al. (2023)
Software-focused devices (N = 19)	Use digital devices to operate computers to learn AI	Scratch and Kitten, Python C++, JavaS-cript, Quick and Draw, ML-Rock Paper Game, ML Quest, Colab, RapidMiner, Prolog, Snap	–	Dai et al. (2023); Gong et al. (2020); Li and Song (2019)	Estevez et al. (2019); Kahn et al. (2018); Yoder et al. (2020)
Hardware-focused devices (N = 10)	Use physical devices to learn AI	Lego Mindstorms, Jibo and PopBots, Lawn bowling robot, Alpha dog robot, Raspberry Pi Raspbian	Heinze et al. (2010); Williams et al., (2019a, 2019b)	Ali et al. (2019); Ho et al. (2019); Lin et al. (2021)	Chai et al. (2020); Chiu et al. (2021); Gong et al. (2018)
Unplugged learning(N = 6)	Uses learning activities to learn AI without any technological devices	Writing stories with robots, paper prototyp-ing activities, role-playing games, debates, board games	Heinze et al. (2010); Lucas (2009)	Ali et al. (2019); Ng et al. (2022); Henry et al. (2021)	Gunasilan (2021)

which introduces the power of the IBM Watson engine for AI modelling (Fernández-Martínez et al., 2021), Cognimates (Sabuncuoglu, 2020; Fernández-Martínez et al., 2021), which allows students to practice coding, and Ecraft2Learn, which contains a deep learning functionality (Kahn et al., 2018), have also been used in secondary school classrooms. Intelligent agents often offer students hands-on experience to develop datasets and to build customized machine learning systems.

Software devices

Software devices are adopted to enable mostly primary and secondary school students to learn about computational thinking, including programming for sequences, rule-based and conditional mechanisms, as well as data science and machine learning using visual language. For example, Scratch, a block-based programming software, is frequently used in both primary (Dai et al., 2023; Li & Song, 2019; Shamir & Levin, 2021) and secondary schools (Estevez et al., 2019; Fernández-Martínez et al., 2021). Other software is used for visualizing and scaffolding abstract AI concepts through online games and experiences, such as Quick and Draw (Martins et al., 2023) and Music Box (Han et al., 2018). In primary schools, Kitten is used to teach block-based programming (Li & Song, 2019), whereas C++ and JavaScript are used for logical thinking and simulation (Gong et al., 2020). In secondary schools, researchers have often employed free online software and tools, such as Snap (Yoder et al., 2020) and Python (Gong et al., 2018; Norouzi et al., 2020), for algorithm automation, as well as RapidMiner for no-code data science learning (Sakulkueakulsuk et al., 2018). To introduce machine learning concepts to secondary school students, other researchers have focused on developing online games such as the Rock Paper Game (Kajiwara et al., 2023) and the 3D role-player video game Quest (Priya et al., 2022).

Hardware devices

In addition, hardware, such as robotics and physical artifacts, has also been used with built-in software to supplement students' understanding of AI concepts. Williams et al. (2019a, 2019b) introduced a preschool originated programming platform consisting of a social robot (PopBot) and a block-based programming interface. In Williams et al. (2019a), 80 prekindergartens to second-grade children (aged four to seven) were asked to build their own LEGO robot characters by using DUPLO block programming. PopBot is used as a learning companion to demonstrate its human-like behavior and to demystify AI concepts to younger students.

The lawn bowling robot (Ho et al., 2019), Zhorai conversational robot (Lin et al., 2020), Micro: Bits (Lin et al., 2021), and Plush toys (Tseng et al., 2021) have been used in primary schools, while CUHKiCar (Chiu et al., 2021), the Alpha robot dog (Chai et al., 2020), Raspberry Pi Raspbian and a four-wheel drive chassis (Gong et al., 2018) have been used in secondary schools. For example, in Ho et al. (2019), grade six students built lawn-bowling robots for games and competitions while learning about the binary search and optimization algorithms of machine learning. Chiu et al. (2021) introduced the robotic CUHKiCar to secondary school students so that they could perform face-tracking and line following tasks.

RQ2: What pedagogical strategies are commonly proposed by studies on AI K-12 learning tools?

As shown in Fig. 5, the four orientations of pedagogy are summarized as authentic/constructive, reflective, didactic, and unplugged. While a total of 17 potential pedagogical strategies were identified within the four orientations in K-12 contexts (Table 5), authentic/constructive methodologies with project-based learning (N = 27) were the most popular pedagogy used across kindergartens (Williams et al., 2019a, 2019b), primary schools (Toivonen et al., 2020; Rodríguez-Garciá et al., 2021), and secondary schools (Gong et al., 2018; Kilhoffer et al., 2023; Sakulkueakulsuk et al., 2018). When teaching AI to students with a diverse range of needs, the evidence demonstrates the positive impact of combining multiple pedagogical approaches in K-12 studies (Heinze et al., 2010; Lee et al., 2021; Williams et al., 2019a, 2019b).

First, authentic and constructive methodologies, project-based (N = 27), human-computer interaction (N = 7), and play-based active learning (N = 5) approaches have been commonly used in K-12 education. Offering hands-on opportunities to students to learn about real-world applications of AI is an example of project-based learning (Fernández-Martínez et al., 2021; Han et al., 2018; Williams et al., 2019a). Other researchers have examined whether students can acquire AI knowledge on human-computer interactive experiences and have found that this does not require any prior knowledge of AI models, such as Zohari (Melsión et al., 2021) and Google Teachable Machine (Lin et al., 2020; Vartiainen et al., 2020). In addition, child-centered play-based learning can effectively engage students and encourage them to take the initiative to construct knowledge during the process of imaginative play (Heinze et al., 2010), which involves students adopting the role of AI developer, tester, and AI robot (Henry et al., 2021).

Fig. 5 Four orientations of pedagogical strategies commonly used in AI K-12 education

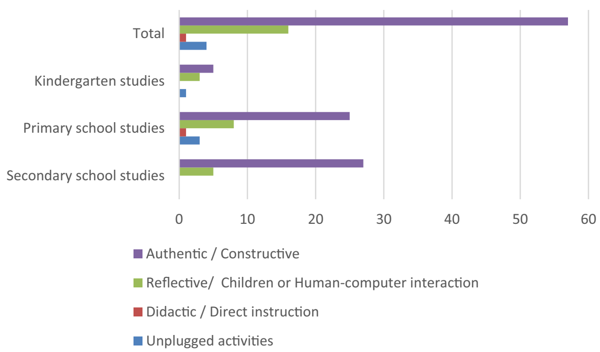

Table 5 Four orientations of the pedagogical strategies used in AI K-12 learning tools studies

Four orientations	Descriptions	Kindergarten (Sample studies)	Primary school (Sample studies)	Secondary school (Sample studies)	
I. Authentic/constructive pedagogy	Emphasis on students' hands-on projects relevant to real-world problems, is the key to understanding				
Collaborative learning	Involve groups of students, peers, or teachers working together towards a common educational goal (Smith & MacGregor, 1992)	–	Lee et al. (2020)	Kaspersen et al. (2021); Sakulkueakulsuk et al. (2018); Wan et al. (2020)	N = 6
Experiential learning	Involve experiencing, reflecting, thinking, and acting (Kolb & Kolb, 2009)	–	Melsión et al. (2021); Shamir and Levin (2021)	Chiu et al. (2021); Estevez et al. (2019); Gunasilan (2021); Kahn et al. (2018)	N = 6
Game-based learning	The application of specific game elements to real-world settings (Trybus, 2015)	–	Han et al. (2018); Lee et al. (2020); Voulgari et al. (2021)	Kajiwara et al. (2023); Priya et al. (2022)	N = 5
Inquiry-based learning	A process of discovering new causal relationships, with students developing hypotheses and verifying them through experiments and/or observations (Pedaste et al., 2015)	–	Ng et al. (2022)	–	N = 1
Participatory learning	A systemic process influenced by children's interest in, and responsiveness to, the object of their activity, and the behaviors and feelings of others (Berthelsen, 2009)	Vartiainen et al. (2020)	–	–	N = 1

Table 5 (continued)

Four orientations	Descriptions	Kindergarten (Sample studies)	Primary school (Sample studies)	Secondary school (Sample studies)	
Play-based learning	A child-directed learning which utilizes play as a learning context (Danniels & Pyle, 2023)	Heinze et al. (2010)	Henry et al. (2021); Tseng et al. (2021)	Gunasilan (2021); Martins et al. (2023)	N = 5
Problem-based learning	Involve students to solve challenging, realistic problems while being guided by teachers (Hung et al., 2008)	–	Lee et al. (2020); Mariescu-Istodor and Jormanainen (2019)	Lee et al. (2021); Yoder et al. (2020)	N = 4
Project-based learning	Engage students through an extended inquiry process based on challenging and authentic questions, and carefully created products and activities (Markham et al., 2003)	Heinze et al. (2010); Williams et al. (2019a, 2019b)	Ali et al. (2019); Rodríguez-Garciá et al. (2021); Shamir and Levin (2022)	Fernández-Martínez et al. (2021); Kilhoffer et al. (2023); Sakulkueakulsuk et al. (2018)	N = 27
II. Reflective pedagogy	Allow students to reflect on their life, knowledge, and prior experience with metacognitive reflections				
Analogy-based approach	To introduce AI concepts to students by building connections to daily-life experiences (Keri & Elbatarny, 2021)	–	Dai et al. (2023)	–	N = 1
Children-computer interaction	An interactive process between students and computers (Hourcade, 2015)	Vartiainen et al. (2020 ;Williams et al., (2019a, 2019b)	Lin et al. (2020); Melsión et al. (2021); Tseng et al. (2021)	Wan et al. (2020)	N = 7

Table 5 (continued)

Four orientations	Descriptions	Kindergarten (Sample studies)	Primary school (Sample studies)	Secondary school (Sample studies)	
Learning by design	Imagine and test the innovative tools and learning environments allowing students to be creative designers of learning experiences in collaboration with their peers (Cope & Kalantzis, 2016)	–	Shamir and Levin (2022); Toivonen et al. (2020)	–	N = 2
Learning by teaching	Allow the internalization and externalization of knowledge by involving students in teaching others (Bargh & Schul, 1980)	–	Lin et al. (2020)	–	N = 1
Online synchronous learning	Allow students to use multiple forms of media and IT in real time (Finkelstein, 2006)	–	–	Ng and Chu (2021); Perach and Alexandron (2022)	N = 2
Programming	Use computer science concepts such as abstraction and decomposition as well as focusing on designing and implementing solutions to computational challenges (Lye & Koh, 2014)	–	Li and Song (2019)	Estevez et al. (2019); Kahn et al. (2018)	N = 3
III. Didactic pedagogy	Strong academic focus, but only to the extent of demonstrating with the correct answers, applications, theorems, and procedures				
Didactic/direct instruction	Students are passive receptors of knowledge and the teacher selects activities (Smerdon et al., 1999)	–	Lin et al. (2021)	–	N = 1

Table 5 (continued)

Four orientations	Descriptions	Kindergarten (Sample studies)	Primary school (Sample studies)	Secondary school (Sample studies)	
IV. Unplugged	Intend to teach AI concepts and related computational thinking skills without employing any digital tools and computational devices (Battal et al., 2021)				
Unplugged activities	–	Lucas (2009)	Ali et al. (2019); Ho et al. (2019)		N = 3
Storytelling	Arouse students' interest, provide a structure for remembering the content material, and share information (Green, 2004)	–	Tseng et al. (2021)	–	N = 1

Pedagogical strategies in kindergartens

Researchers have often used project-based approaches (N = 3), human-computer interactions (N = 3), play-based learning (N = 1), and unplugged activities (N = 1) to teach younger students AI concepts. In a project-based learning approach, students learn by actively engaging in real-world projects. Williams et al. (2019a, 2019b) used a hands-on project allowing prekindergarten and kindergarten students to acquire AI concepts, including knowledge-based systems, supervised machine learning, and AI generative music. Alternatively, Vartiainen et al. (2020) studied human-computer interactions that allowed students to freely explore the input−output relationship with Google Teachable Machine to identify and to evaluate a problem and find a solution to it. Heinze et al. (2010) focused on imaginative play, which is relevant to young students, as play is associated with various levels of autonomy and provides an engaging introduction to AI and the formation of scientific concepts. Lucas (2009) used unplugged activities to teach the key concepts of computing, including data encoding, data compression, and error detection.

Pedagogical strategies in primary schools

Project-based learning is more frequently used in primary schools than in kindergartens: It has been reported as a learning approach in 14 of the 18 studies of primary school settings, compared to only three of the five studies in the kindergarten setting. Similarly, in primary school settings, studies have revealed a strong dependence on play/game-based (N = 5) and human-computer interaction learning approaches (N = 3).

Projects that demonstrate students' improved AI knowledge have been conducted. Machine learning projects (Toivonen et al., 2020), LearningML projects (Rodríguez-Garciá et al., 2021), and "AI+" projects (Han et al., 2018) have been designed to demystify AI knowledge. Henry et al. (2021) integrated machine learning in role-playing games, while Shamir and Levin (2021) allowed students to play with AI chatbots to develop AI models and to construct a rule-based machine-learning system. Some researchers have designed learning programs that offer human-computer interaction activities to educate students about gender bias (Melsión et al., 2021) and the social impact of mistakes made by AI models in training datasets (Lin et al., 2020).

Pedagogical strategies in secondary schools

The project-based learning approach (N = 10) is also the most dominant in secondary schools, followed by collaborative learning (N = 5). First, project-based learning is used to engage students by applying their AI knowledge to solve real-world problems. Teachers have reported that AI projects and hands-on activities are effective in keeping students focused on tasks (Kilhoffer et al., 2023). For example, a smart car-themed AI project (Gong et al., 2018), the Redesign YouTube project (Fernández-Martínez et al., 2021), and the agriculture-based AI Challenge project (Sakulkueakulsuk et al., 2018) have been introduced to provide hands-on experience for students to connect their knowledge to their day-to-day lives. Through active exploration, such projects prompt secondary school students to contemplate the personal, social, economic, and ethical consequences of AI technologies (Kaspersen et al., 2021).

Second, collaborative learning allows students to work in groups to promote cognitive knowledge, as it engages them in scientific inquiry with the help of smart devices (Wan et al., 2020). Kaspersen et al. (2021) designed a collaborative learning tool, VotestratesML, together with a voting project allowing students to build machine learning models based on real-world voting data to predict results.

RQ3: What learning outcomes have been demonstrated in studies on AI K-12 learning tools?

Of the 46 articles, 31 reported potential learning outcomes: (1) cognitive outcomes, (2) affective and behavioral outcomes, and (3) the level of course satisfaction and soft skills acquisition.

Cognitive outcomes

Thirty-one studies documented various degrees of positive cognitive outcomes. Students generally showed a basic understanding of AI, including AI rule-based systems (Ho et al., 2019), machine learning principles and applications (Han et al., 2018; Shamir & Levin, 2021), AI ethics (Melsión et al., 2021), and AI limitations (Lin et al., 2020). In Williams et al. (2019a), 70% of prekindergarten and kindergarten students understood knowledge-based systems, whereas Vartiainen et al. (2020) found that, through AI learning tools, younger students developed their computational thinking and their understanding of machine-learning principles and applications. Then, Dai et al. (2023) reported that primary school students taught with analogy-based pedagogy (i.e., using humans as a reference to teach and learn AI) significantly outperformed primary school students taught with the conventional direct instructional approach in terms of developing their conceptual understanding and increasing their AI technical knowledge proficiency as well as their ethical awareness of AI. Other researchers have argued that primary school students have demonstrated their understanding of AI by constructing and applying machine-learning algorithms with the help of digital role-playing games (Voulgari et al., 2021) and project-based pedagogy (Shamir & Levin, 2021). Through designing and programming a robot, students increased their understanding of AI biases (Melsión et al., 2021). In secondary schools, researchers have also reported an increase in students' knowledge of AI algorithms (Yoder et al., 2020) and machine learning concepts (Sakulkueakulsuk et al., 2018), as well as their recognition of AI patterns (Wan et al., 2020). For example, students understood the fundamental neural networks of machine learning concepts by developing a classification model of recycling images (Martins et al., 2023).

Affective and behavioral outcomes

Affective and behavioral outcomes have been identified in AI learning tool studies within K-12 contexts. In general, students' motivation to learn AI (Han et al., 2018; Shamir & Levin, 2021, 2022) and their interest in the course (Mariescu-Istodor & Jormanainen, 2019; Martins et al., 2023) were enhanced as a result of AI learning activities. Students' perceptions of the relevance of AI to their life also increased (Kajiwara et al., 2023; Lin et al., 2021). Students scored high on self-efficacy (Kajiwara et al., 2023; Shamir & Levin, 2022) and confidence (Shamir & Levin, 2021) in training and validating an AI system. In Martins et al. (2023), over 45% of 108 secondary school student participants in the introductory course "Machine Learning for all" reported that they perceived AI learning as an enjoyable experience, and 63% of them hoped to learn more about machine learning in the future.

Moreover, students reported that they were highly motivated to explore the Teachable Machine (Vartiainen et al., 2020), to design the robotic arm and computer source codes (Ho et al., 2019), to draw animals and sea creatures for the machine learning project (Mariescu-Istodor & Jormanainen, 2019), and to predict the sweetness of mangoes by using machine learning models (Sakulkueakulsuk et al., 2018).

From the behavioral perspective, high student engagement was reported in project-based (Kaspersen et al., 2021; Shamir & Levin, 2021; Wan et al., 2020) and play/game-based (Heinze et al., 2010; Voulgari et al., 2021) settings. Primary students attended all sessions and expressed a desire to join an upcoming AI contingency course (Shamir & Levin, 2021), while secondary students were actively engaged in scientific inquiry (Wan et al., 2020). Students were also keen on recommending AI games to their friends (Voulgari et al., 2021). Therefore, a combination of play/game-based and project-based approaches may consolidate AI concepts through gameplay while enhancing students' engagement in AI projects (Han et al., 2018).

Level of satisfaction and soft skills acquisition

Students' level of satisfaction was found to be positively influenced by constructivist (e.g., project-based) and reflective (e.g., learning by design and learning by teaching) pedagogies (Ho et al., 2019; Shamir & Levin, 2021, 2022). In Lin et al. (2020), students reported a high satisfaction level upon acquiring AI knowledge. Their computational thinking and subsequent project performance were also enhanced. All students completed the course and their AI tasks without any previous learning experience (Toivonen et al., 2020).

The findings from the selected articles reveal that a deep understanding of AI promotes the acquisition of various soft skills. Ali et al. (2019) found that students' intellectual curiosity increased after engaging in the construction of an AI neuron. By using bulletin boards shared electronically and online chats for feedback, their collaboration and communication skills were also enhanced (Shamir & Levin, 2021). Moreover, students reported gaining problem solving and technical skills when working with AI systems, including coding, designing simple algorithms, and debugging in Scratch learning activities (Dai et al., 2023).

RQ4: What were the research and assessment methods used in AI K-12 learning tools studies?

In this section, an overview is presented of research methods and data collection procedures within K-12 contexts. Overall, researchers adopted a mixed method (N = 19), qualitative (N = 15) and quantitative methods (N = 12) in AI learning tools in K-12 research. Mixed methods are predominantly used in both primary school (e.g., Dai et al., 2023; Martins et al., 2023; Shamir & Levin, 2021; Toivonen et al., 2020) and secondary school contexts (e.g., Chiu et al., 2021; Estevez et al., 2019), whereas qualitative methods are commonly used in kindergartens (e.g., Heinze et al., 2010; Vartiainen et al., 2020), as shown in Table 6.

A variety of assessment methods were used: questionnaires and surveys (N = 30), artifacts/performance-based evaluation (N = 15), interviews (N = 14), observations (N = 5), games assessment (N = 1), and field visits (N = 1) (Table 7). The two most commonly used data collection methods - questionnaires and surveys and artifacts/performance-based evaluation - are discussed in this section.

In terms of assessment methods, questionnaires and surveys (N = 30) and artifacts/performance-based evaluation (N = 17) are the two most commonly used data collection methods across K-12 contexts (Table 7).

Questionnaires and surveys are used in a quantitative methodology to understand the perception of robotics and theory of mind (e.g., knowledge access, content false belief and explicit false belief). For example, perception of robotics and theory of mind were used in kindergartens (Williams et al., 2019a, 2019b).

Surveys were used to evaluate primary school students' motivation (Lin et al., 2021), self-efficacy in AI learning (Shamir & Levin, 2022), and perceived knowledge and competence (Dai et al., 2023; Mariescu-Istodor & Jormanainen, 2019; Ng et al., 2022). In addition to Ali et al. (2019), who used the Torrance test for assessment, researchers also utilized pre- and posttests (Tseng et al., 2021) to compare the AI learning outcomes of control and treatment groups in primary school settings (Melsión et al., 2021). Others provided AI educational experience without stating the assessment method (Ho et al., 2019; Lee et al., 2020; Tseng et al., 2021). Heinze et al. (2010) conducted AI learning activities without assessing learning outcomes. Shamir and Levin (2022) designed a questionnaire based on "constructionist validated robotics learning" for machine learning construction (the questionnaire included statements such as "*I can make a ML system*", "*I can propose ideas for using ML to solve problems*."). Dai et al. (2023) used multiple choice questions (e.g., "*Which of the following devices or systems is an intelligent agent?*") to evaluate the AI knowledge of primary school students according to Bloom's Taxonomy.

In secondary schools, surveys are used to measure students' information knowledge acquisition (Priya et al., 2022), perceived abilities (Chiu et al., 2021; Ng & Chu, 2021) and futuristic thinking, engagement, interactivity, and interdisciplinary thinking skills (Sakulkueakulsuk et al., 2018). For example, in Priya et al. (2022), surveys were used in the first phase of their study to test the knowledge gained by students in three AI areas, namely, supervised learning (e.g., "*What is the underlying idea behind supervised learning*?"), gradient descent (e.g., "*In gradient descent how do we reach optimum point?*"), and KNN classifications (e.g., "*Using underlying*

Table 6 An overview of the research methods within K-12 contexts

Research method		Kindergarten (Sample studies)	Primary school (Sample studies)	Secondary school (Sample studies)
Mixed method	N = 19	/	Dai et al. (2023); Shamir and Levin (2021); Toivonen et al. (2020)	Ng and Chu (2021); Norouzi et al. (2020); Martins et al. (2023)
Qualitative	N = 15	Heinze et al. (2010); Lucas (2009); Vartiainen et al. (2020)	Henry et al. (2021); Lee et al. (2020); Li and Song (2019)	Kaspersen et al. (2021); Kilhoffer et al. (2023); Yoder et al. (2020)
Quantitative	N = 12	Williams et al. (2019a, 2019b)	Lin et al. (2020); Rodríguez-García et al. (2020, 2021)	Fernández-Martínez et al. (2021);Kajiwara et al. (2023); Priya et al. (2022)

Table 7 An overview of the data collection procedures within K-12 contexts

Data collection		Kindergarten (Sample studies)	Primary school (Sample studies)	Secondary school (Sample studies)
Survey and questionnaires	N = 31	Perception of Robots Questionnaires (*"Robots follow rules/robots do not follow rules"*; *"I am smarter than robots/robots are smarter"*) (Williams et al., 2019a)	Questionnaire based on constructionist validated robotics learning (*"I can make a ML system"*; *"I can propose ideas for using ML to solve problems"*) (Shamir & Levin, 2022)	Assessed the concept of supervised learning (e.g. *"What is the underlying idea behind Supervised Learning?"*), gradient descent (e.g. "*In gradient Descent how do we reach optimum point?"*), and KNN classifications (e.g. *"Using underlying principle of KNN classification classify a fruit which is surrounded by 2 apples and 1 mango in its 3 nearest neighbors."*) (Priya et al., 2022)
Artefact/performance-based	N = 15	Examined the tablet interaction logs, the number of interactions, and the time spent undertaking each learning activity (Williams et al., 2019a)	Drawing assessment to evaluate students' understanding and cognitive development about AI (Dai et al., 2023)	Evaluate block-based programming artefacts from breadth-first search (Yoder et al., 2020)
Interviews/focus group	N = 14	Interviewed students to understand the process of teaching machines to learn (e.g. "*What does the computer see?" "What does the computer do?"*) (Vartiainen et al., 2020)	Asked teachers about their previous experience with computer science and coding (e.g. *"Do you need to help you be successful in teaching computer science and AI to your classes"*) (Lee et al., 2020)	Understand students' learning experience (e.g. *"When learning clustering analysis, what challenges you the most?"*) (Wan et al., 2020)
Observation	N = 5	Video data showing how students teach computers to learn (Vartiainen et al., 2020)	Video recording of the online workshop showing how students constructed their machine learning models (Tseng et al., 2021)	Two silent peer observers providing feedback in four areas: engagement in design and implementation; teaching and supporting learning; assessment; and learning environment (Gunasilan, 2021)
Games	N = 1	/	/	Evaluate the game based on the four factors of the Technological Acceptance Model (e.g. perceived ease of use, usefulness, intention to use, and correctness) (Priya et al., 2022)

Table 7 (continued)

Data collection		Kindergarten (Sample studies)	Primary school (Sample studies)	Secondary school (Sample studies)
Field visit	N = 1	/	Field visits to a number of urban and suburban public and private schools in China (Gong et al., 2020)	/

principle of KNN classification classify a fruit which is surrounded by 2 apples and 1 mango in its nearest neighbors."). In the second phase of the study, surveys were used to evaluate students' satisfaction with the design of the game "ML Quest", which introduced machine learning concepts based on the quality factors of the technological acceptance model (e.g., *"Visualizations displayed by ML-Game are relevant to the concept taught at each level"*).

Artifact-based/performance-based assessments are embedded in a large number of studies to evaluate learning outcomes. Through artifacts (e.g., Popbots), Williams et al., 2019a, 2019b) evaluated kindergarteners' knowledge and understanding of supervised machine learning. Ho et al. (2019) used a performance-based assessment to assess primary students' understanding of optimal data training and its AI applications. The artifact analysis of Shamir and Levin (2021) involved the construction of a rule-based AI system, which included designing, understanding, and creating the AI neural network agent. Dai et al. (2023) used a drawing assessment to evaluate primary school students' understanding of AI and its impact on their cognitive development using prompt questions (e.g., "*What AI can do? What would you like to use AI for?*") to stimulate their thinking.

Moreover, Yoder et al. (2020) focused on secondary school students' block-based programming artifacts to examine their knowledge of AI search algorithms and breadth-first search (BFS), as well as their understanding of the possibility of gender bias when using AI screening tools in recruitment. In Martins et al. (2023), machine learning model artifacts created by students were used as evidence to demonstrate their learning outcomes. The performance-based assessment was used to evaluate students' ability to correctly label the recycling trash images in the classification process.

Discussion and conclusion

The results of this study are consistent with Kandlhofer et al. (2016), who found that a variety of learning tools have been designed to support various learning objectives for students from kindergarten to university. The previous literature also indicates that many learning tools, such as intelligent agents and software, are effective in facilitating adolescents' and university students' acquisition of computational thinking skills (Çakiroğlu et al., 2018; Van Brummelen et al., 2021), whereas the availability of such tools for kindergarten and primary students is often overlooked. Few researchers have investigated whether AI learning tools can bridge the learning gap of younger students (Zhou et al., 2020). This study revealed that without prior programming experience, these learning tools (such as Popbots, Teachable Machine, and Scratch) can help address the diverse needs of younger students across K-12 educational levels (Resnick et al., 2005), leading to a richer visual learning experience and improving instructional quality (Kaspersen et al., 2021; Long & Magerko, 2020).

Previous reviews have indicated that many pedagogies are suitable in AI education, although this was done without reference to students' learning outcomes (Sanui & Oyelere, 2020). The findings of this study enrich existing knowledge of the positive effects of authentic and constructivist pedagogies in affective, behavioral, and cognitive aspects, as well as students' level of satisfaction in AI learning. This study reveals that multiple pedagogies, such as project-based learning, experiential learning, game-based learning, collaborative learning, and human–computer interaction, are widely used in K-12 educational settings. An emerging form of analogy-based pedagogy to evaluate the AI knowledge of primary school students by assessing their drawings is identified. The focus of this analogy-based pedagogical strategy is the comparison of humans and AI, where humans are gradually moved from an analogy and to a contrast to highlight the characteristics, mechanism, and learning procedures of AI. It demonstrates and reflects the dialogic quality of the relationship with shared enquiry and shared thinking among students and AI learning tools. This is significant given the new cognitive demand of the AI era, as it provokes a shift in the role of the students by thinking together and learning to learn together (Wegerif, 2011). In future studies, exploration of additional emerging pedagogies (Yim, 2023), the co-creation of arts-based possibility spaces (Burnard et al., 2022), and dialogic learning spaces (Wegerif, 2007) in AI literacy education can be considered.

In addition, educational tools and applications are used not only to contribute new ways of knowing and doing but also to embed learning tools at the center of the AI literacy activities and programs instead of playing a supporting role in the primary purpose of education. This is expanding to serve the human need for education. The use of multiple educational learning tools and pedagogical strategies may be influenced by various factors in the teaching process, including students' gender, background knowledge, and educational setting, all of which may affect their learning styles and motivation to learn AI. These factors and issues can be explored in future studies.

In this review, it was found that some studies assessed students' performance by using the Torrance test for creativity (Ali et al., 2019), an AI knowledge test (Ng et al., 2022; Wan et al., 2020), pre- and postsurveys (Chiu et al., 2021; Estevez et al., 2019), and comparisons between control and treatment groups (Dai et al., 2023; Melsión et al., 2021), while others used subjective measures, including self-report surveys. Although artifact-based and performance-based approaches have been increasingly adopted in data collection procedures, some researchers used them as evidence of learning, without scoring according to established marking criteria for assessment purposes. There is room for introducing objective and rubric-based evaluation mechanisms to assess the quality of suggested methodologies. However, the lack of agreement on assessment criteria and instructional feedback shows that further research is needed to support the wide application of AI teaching in K-12 classrooms.

Research implications

From this study, the use of intelligent agents is recommended, including Teachable Machines, Machine Learning for Kids, and Learning for ML. Kindergarten students can benefit from learning tools such as PopBots, while software devices such as

Scratch and Python can be introduced to demystify core AI principles to primary school students and create AI-driven solutions and models for secondary school students. Although hardware such as robotics and physical artifacts are generally effective, they may be costly for scalability.

This review reveals that constructivism, constructionism, and computational thinking are instrumental in addressing AI literacy education. Unfortunately, little research has adopted theoretical frameworks or conceptual models of reference for AI curricula, educational activities, or the design of AI learning tools and applications. To guide teaching, learning and effectiveness in using AI learning tools within AI literacy education, AI literacy learning theoretical frameworks are needed to guide the teaching instruction of kindergarten, primary and secondary school students. Usability, AI ethics, and transparency must be addressed in tool design to ensure that issues pertaining to data privacy and security will not arise. Moreover, there is currently insufficient theory-based, rigorous research on the effectiveness of AI educational tools to meet the diverse learning needs of students. Children may be invited to codesign with application designers. Thus, researchers may conduct theory-based and outcome-oriented quantitative and qualitative research on AI educational tools, which may be significantly beneficial to students.

More evaluation and documented analysis regarding the effectiveness of learning tools should be conducted to inform stakeholders of the existing trends in the field, pedagogical strategies, and instructional methods for teacher professional development.

More research, analysis, and evidence are needed to determine the effectiveness of AI learning tools before they are scaled up based on a risk-benefit analysis. Researchers should also clearly define the educational settings in which specific AI learning tools are appropriate to support the effective delivery of AI content in the classroom.

Recommendations

For educators

Aside from providing students with AI knowledge and skills that the market demands (Burgsteiner et al., 2016) and encouraging all citizens to be AI literate (Goel, 2017; Pedro et al., 2019), educators may promote holistic AI literacy education by considering humans, nonhumans (e.g., animals and machines) (Yim, 2023) and environmental elements (Miao & Shiohira, 2022) in their teaching content. Ethical questions should also be considered, including inclusivity, fairness, responsibility, transparency, data justice, and social responsibility (Crawford, 2021; Benjamin, 2019). To provide a roadmap for sustainable AI education implementation and development, it is essential to involve teachers in the design of learning tools and understand their perceptions regarding AI literacy education, as well as provide pedagogical strategies, resource development, and needs-based professional training for both preservice and in-service teachers.

For teachers

Children learn best at a certain stage of cognitive development (Ghazi & Ullah, 2015). It is recommended that the content of instruction is consistent with students' cognitive developmental level, as it influences their readiness and ability to learn (Piaget, 2000). As a result, the technical and content depth of the educational learning tools should align with students' age and the teaching objectives, and teachers should understand students' cognitive development to plan age-appropriate activities with suitable learning tools. More collaboration among teachers with various pedagogical experiences across various educational levels may lead to more innovative and efficient teaching processes.

For researchers

Researchers should report evidence of the reliability. and validity of their findings where applicable since such data are crucial to evaluating the quality of their recommended learning tools or pedagogies. This can also aid other academics in updating their research on existing and developing pedagogical strategies. Researchers may consider designing and developing a standardized AI assessment mechanism that can be used across different grade levels to compare students' AI literacy. This approach permits the standardization of assessment criteria and instructional feedback and thus better supports the wider application of AI teaching in K-12 classrooms.

Appendix 1: Overview of the selected articles

Author	Research methods	Learning tools	Pedagogies	Country	Education Level
Williams et al. (2019a)	Quantitative	PopBots	Project-based learning; human–computer interaction	USA	Kindergarten and pre-kindergarten
Williams et al. (2019b)	Quantitative	PopBots	Project-based learning; human–computer interaction	USA	Kindergarten and pre-kindergarten
Heinze et al. (2010)	Qualitative	Writing stories with robots and Lego Mindstorms; JavaScript to program robots and computer games	Project-based learning; play-based learning	Australia	K-6

Author	Research methods	Learning tools	Pedagogies	Country	Education Level
Lucas (2009)	Qualitative	csunplugged.org—unplugged activities	Unplugged activity	New Zealand	K-6
Vartiainen et al. (2020)	Qualitative	Google Teachable Machine	Participatory learning; human–computer interaction	Finland	Kindergarten and primary school
Ali et al. (2019)	Mixed	Jibo, PopBots, Google Teachable Machine, paper prototyping activity, Droodle creativity game and abstract drawing	Project-based learning; unplugged activities	/	Primary school
Dai et al. (2023)	Mixed	Scratch, Machine Learning for Kids	Analogy-based learning	China	Primary school
Gong et al. (2020)	Mixed	AI-in-a-Box, Squirrel AI, Scratch and Kitten, Python C++, JavaScript AI textbooks	Project-based learning	China	Primary school
Han et al. (2018)	Qualitative	Music box mobile application	Project-based learning; game-based learning	China	Lower primary school
Ho et al. (2019)	Qualitative	Disney princesses, Lego Mindstorms EV3 kit, lawn bowling robot	Project-based learning; unplugged activities	Australia	Upper primary school
Lee et al. (2020)	Qualitative	PRIMARY AI tools	Project-based learning; game-based learning; problem-based learning; collaborative learning	/	Upper primary school
Lin et al. (2020)	Quantitative	Zhorai	Learn by teaching; human–computer interaction	USA	Primary school

Author	Research methods	Learning tools	Pedagogies	Country	Education Level
Lin et al. (2021)	Quantitative	AI curriculum textbook (Qin et al., 2019) issued by the local education authority, and a device similar to Micro:bit	Direct instruction, followed by hands-on activity	China	Upper primary school
Melsión et al. (2021)	Mixed	Grad-CAM explainability technique in an image captioning system(https://biaix.now.sh); Google Teachable Machine	Project-based learning; experiential learning; human–computer interaction	Sweden	Upper primary school
Ng et al. (2022)	Mixed	Story Jumper (digital story creations tool), AI ocean activity (website: code.org), Quick Draw, Google Teachable Machine, Kahoot, Siri, AI translation and AI-driven robots	Inquiry-based learning	Hong Kong	Primary school
Shamir and Levin (2021)	Mixed	Scratch	Project-based learning; programming; experiential learning	Israel	Upper Primary
Shamir and Levin (2022)	Mixed	AI Chatbot; the Code.org platform for algorithm creation; the Mitsuku website for AI conversation; Scratch; IBM Watson engine	Project-based learning; learning by design	/	Upper Primary
Toivonen et al. (2020)	Mixed	Google Teachable Machine, web applications with HTML5 and JavaScript	Project-based learning; learning by design	Finland	Upper Primary

Author	Research methods	Learning tools	Pedagogies	Country	Education Level
Tseng et al. (2021)	Qualitative	PlushPal	Play-based learning; story-telling; human–computer interaction	Japan	Primary school
Voulgari et al. (2021)	Mixed	Artbot (an educational game design employed on the Learn ML website http://learnml.eu/games.php)	Game-based learning	Greece	Primary and secondary school
Henry et al. (2021)	Qualitative	Role-playing games	Project-based learning; play-based learning	/	Primary and lower secondary school
Mariescu-Istodor and Jormanainen (2019)	Qualitative	Web application (HTML and JavaScript), YouTube learning videos, hand-drawn illustration	Project-based learning; problem-based learning	Finland	Primary and secondary school
Li and Song (2019)	Qualitative	Scratch	Programming	China	Primary and secondary school
Rodríguez-García et al. (2020)	Quantitative	LearningML platform	Project-based learning	/	Primary and secondary school
Rodríguez-Garciá et al. (2021)	Quantitative	LearningML platform	Project-based learning	Spain	Primary and secondary school
Chai et al. (2020)	Quantitative	Alpha dog robot	/	China	Secondary school
Chiu et al. (2021)	Mixed	Jupyter, Blockly, WebApps cognitive services, google teachable machine, CUHKiCar (self-developed robotic car)	Experiential learning; collaborative learning	Hong Kong	Lower secondary school
Estevez et al. (2019)	Mixed	Scratch	Experiential learning: Project-based learning	Spain	Upper secondary school

Author	Research methods	Learning tools	Pedagogies	Country	Education Level
Fernández-Martínez et al. (2021)	Quantitative	Scratch, Machine Learning for kids, Cognimates	Project-based learning	Spain	Lower secondary school
Gong et al. (2018)	Qualitative	Raspberry Pi Raspbian, Python	Project-based learning; collaborative learning	China	Upper secondary school
Gunasilan (2021)	Mixed	Google collaborator, Python, Excel	Active learning; experiential learning	UK	Upper secondary school
Kahn et al. (2018)	Mixed	Snap!, ecraft2learn	Project-based learning; experiential learning	Indonesia	Upper secondary school
Kajiwara et al. (2023)	Quantitative	Machine Learning-Rock Paper game	Game-based learning	Japan	K-12 and beyond
Kaspersen et al. (2021)	Qualitative	VotestratesML, computational empowerment learning tool	Project-based learning; collaborative learning;	Denmark	Secondary school
Kilhoffer et al. (2023)	Qualitative	Google Teachable Machine, gamified approach (SpotTheTroll.org)	Project-based learning; game-based learning	USA	Secondary school
Lee et al. (2021)	Qualitative	MIT STEP Lab, MIT PRG, Scratch, google classroom	Project-based learning	USA	Lower secondary school
Martins et al. (2023)	Mixed	Quick Draw!; Object Detector and Classifier app, Google Teachable Machine, MIT Moral Machine	Active learning	Brazil	Secondary school
Ng and Chu (2021)	Mixed	AI Ocean; Code,org	Online synchronous learning	Hong Kong	Lower secondary school
Norouzi et al. (2020)	Mixed	Colab	Project-based learning	USA	Upper secondary school
Perach and Alexandron (2022)	Quantitative	Coursera's Deep Learning Specialization	Online synchronous learning	Israel	Upper secondary school

Author	Research methods	Learning tools	Pedagogies	Country	Education Level
Priya et al. (2022)	Quantitative	Machine Learning Quest	Game-based learning; Project-based learning	/	Secondary school
Sabuncuoglu (2020)	Mixed	Cognimates, Machine Learning for Kids, ecraft2learn, YouTube videos	Project-based learning	Norway	Lower secondary school
Sakulkue-akulsuk et al. (2018)	Mixed	RapidMiner	Project-based learning; collaborative learning	Thailand	Lower secondary school
Scherz and Haberman (1995)	Qualitative	Prolog	Project-based learning	Israel	Secondary school
Wan et al. (2020)	Mixed	SmileyCluster	Project-based learning; collaborative learning; human–computer interaction	USA	Upper secondary school
Yoder et al. (2020)	Qualitative	Snap; GPS navigation; coding activities	Problem-based learning	USA	Secondary school

Acknowledgements The support and guidance provided by Professor Rupert Wegerif, Dr Annouchka Bayley, Dr Eleanor Dare and the University of Cambridge during this ongoing academic pursuit have been instrumental and greatly appreciated.

Funding This research has not received any funding.

Declarations

Conflict of interest The authors declare no conflict of interest.

Informed consent Not applicable.

Research involving human participants and/or animals Not applicable.

Ethical statements We hereby declare that this manuscript is the result of our independent creation under the reviewers' comments. Except for the quoted contents, this manuscript does not contain any research achievements that have been published or written by other individuals or groups. We are the only authors of this manuscript. The legal responsibility of this statement shall be borne by us.

References

References marked with an asterisk indicate reports included in this scoping review

*Ali, S., Payne, B. H., Williams, R., Park, H. W., & Breazeal, C. (2019, June). Constructionism, ethics, and creativity: Developing primary and middle school artificial intelligence education. In *International workshop on education in artificial intelligence k-12 (eduai'19)* (pp. 1–4).

Bai, H., & Yang, S. (2019, October). Research on the sustainable development model of information technology literacy of normal students based on deep learning recommendation system. In *2019 4th International conference on mechanical, control and computer engineering (icmcce)* (pp. 837–8373). IEEE.

Bargh, J. A., & Schul, Y. (1980). On the cognitive benefits of teaching. *Journal of Educational Psychology, 72*(5), 593.

Battal, A., Afacan Adanır, G., & Gülbahar, Y. (2021). Computer science unplugged: A systematic literature review. *Journal of Educational Technology Systems, 50*(1), 24–47.

Benjamin, R. (2020). Race after technology: Abolitionist tools for the new Jim code.

Berthelsen, D. (2009). Participatory learning. In *Participatory learning in the early years: Research and pedagogy* (pp. 1–11). Routledge.

Burgsteiner, H., Kandlhofer, M., & Steinbauer, G. (2016). Irobot: Teaching the basics of artificial intelligence in high schools. In *Proceedings of the 30th AAAI conference on artificial intelligence* (pp. 4126–4127). AAAI Press.

Burnard, P., Dragovic, T., Jasilek, S., Biddulph, J., Rolls, L., Durning, A., & Fenyvesi, K. (2022). The art of co-creating arts-based possibility spaces for fostering STE (A) M practices in primary education. In *Arts-based methods in education around the world* (pp. 247–281). River Publishers.

Çakiroğlu, Ü., Suiçmez, S. S., Kurtoğlu, Y. B., Sari, A., Yildiz, S., & Öztürk, M. (2018). Exploring perceived cognitive load in learning programming via Scratch. *Research in Learning Technology, 26*, 1–20.

Cetindamar, D., Kitto, K., Wu, M., Zhang, Y., Abedin, B., & Knight, S. (2022). Explicating AI literacy of employees at digital workplaces. *IEEE Transactions on Engineering Management, 71*, 810–823.

*Chai, C. S., Wang, X., & Xu, C. (2020). An extended theory of planned behavior for the modelling of Chinese secondary school students' intention to learn Artificial Intelligence. *Mathematics, 8*(11), 2089.

Chang, C. C., Hwang, G. J., & Tu, Y. F. (2022). Concept mapping in technology-supported K-12 education: A systematic review of selected SSCI publications from 2001 to 2020. *Journal of Educational Computing Research, 60*(7), 1637–1662.

Chang, C. Y., Lai, C. L., & Hwang, G. J. (2018). Trends and research issues of mobile learning studies in nursing education: A review of academic publications from 1971 to 2016. *Computers & Education, 116*, 28–48.

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *Ieee Access, 8*, 75264–75278.

Chiu, T. K. F., & Chai, C. S. (2020). Sustainable curriculum planning for artificial intelligence education: A self-determination theory perspective. *Sustainability, 12*(14), 5568.

*Chiu, T. K. F., Meng, H., Chai, C. S., King, I., Wong, S., & Yam, Y. (2021). Creation and evaluation of a pre-tertiary Artificial Intelligence (AI) curriculum. *IEEE Transactions on Education*, *65*(1), 30–39.

Cope, B., & Kalantzis, M. (Eds.). (2016). *A pedagogy of multiliteracies: Learning by design*. Springer.

Crawford, K. (2021). *The atlas of AI: Power, politics, and the planetary costs of artificial intelligence*. Yale University Press.

*Dai, Y., Lin, Z., Liu, A., Dai, D., & Wang, W. (2023). Effect of an analogy-based approach of artificial intelligence pedagogy in upper primary schools. *Journal of Educational Computing Research*. https://doi.org/10.1177/0735633123120134.

Danniels, E., & Pyle, A. (2023). Inclusive play-based learning: Approaches from enacting kindergarten teachers. *Early Childhood Education Journal, 51*(7), 1169–1179.

Darmawansah, D., Hwang, G. J., Chen, M. R. A., & Liang, J. C. (2023). Trends and research foci of robotics-based STEM education: A systematic review from diverse angles based on the technology-based learning model. *International Journal of STEM Education, 10*(1), 1–24.

Estevez, J., Garate, G., & Graña, M. (2019). Gentle introduction to artificial intelligence for high-school students using scratch.* *IEEE Access, 7*, 179027–179036.

*Fernández-Martínez, C., Hernán-Losada, I., & Fernández, A. (2021). Early introduction of AI in Spanish middle schools. A motivational study. *KI-Künstliche Intelligenz, 35*(2), 163–170.

Finkelstein, J. E. (2006). *Learning in real time: Synchronous teaching and learning online* (Vol. 5). Wiley.

Ghazi, S. R., & Ullah, K. (2015). Concrete operational stage of Piaget's cognitive development theory: An implication in learning general science. *Gomal University Journal of Research, 31*(1), 78–89.

Goel, A. (2017). AI education for the world. *AI Magazine, 38*(2), 3–4.

*Gong, X., Tang, Y., Liu, X., Jing, S., Cui, W., Liang, J., & Wang, F. Y. (2020, October). K-9 Artificial Intelligence education in Qingdao: Issues, challenges and suggestions. In *2020 IEEE international conference on networking, sensing and control (ICNSC)* (pp. 1–6). IEEE.

*Gong, X., Wu, Y., Ye, Z., & Liu, X. (2018, June). Artificial Intelligence course design: iSTREAM-based visual cognitive smart vehicles. In *2018 IEEE intelligent vehicles symposium (IV)* (pp. 1731–1735). IEEE.

Green, M. C. (2004). Transportation into narrative worlds: The role of prior knowledge and perceived realism. *Discourse Processes, 38*(2), 247–266.

*Gunasilan, U. (2021). Debate as a learning activity for teaching programming: A case in the subject of machine learning. *Higher Education, Skills and Work-Based Learning*, *12*(4), 705–718.

*Han, X., Hu, F., Xiong, G., Liu, X., Gong, X., Niu, X., Shi, W., & Wang, X. (2018). Design of AI+ curriculum for primary and secondary schools in Qingdao. In *2018 Chinese automation congress (CAC)* (pp. 4135–4140). IEEE.

*Heinze, C. A., Haase, J., & Higgins, H. (2010, July). An action research report from a multi-year approach to teaching artificial intelligence at the k-6 level. In *1st AAAI symposium on educational advances in artificial intelligence*.

*Henry, J., Hernalesteen, A., & Collard, A. S. (2021). Teaching Artificial Intelligence to K-12 through a role-playing game questioning the intelligence concept. *KI-Künstliche Intelligenz, 35*(2), 171–179.

*Ho, J. W., Scadding, M., Kong, S. C., Andone, D., Biswas, G., Hoppe, H. U., & Hsu, T. C. (2019, June). Classroom activities for teaching artificial intelligence to primary school students. In *Proceedings of international conference on computational thinking education* (pp. 157–159).

Hourcade, J. P. (2015). *Child–computer interaction*. Self, Iowa City.

Hsu, Y. C., Ho, H. N. J., Tsai, C. C., Hwang, G. J., Chu, H. C., Wang, C. Y., & Chen, N. S. (2012). Research trends in technology-based learning from 2000 to 2009: A content analysis of publications in selected journals. *Journal of Educational Technology & Society, 15*(2), 354–370.

Hung, W., Jonassen, D. H., & Liu, R. (2008). Problem-based learning. In *Handbook of research on educational communications and technology* (Vol. 3(1), pp. 485–506). Erlbaum Associates.

*Kahn, K. M., Megasari, R., Piantari, E., & Junaeti, E. (2018). AI programming by children using snap! Block programming in a developing country. In *EC-TEL practitioner proceedings 2018: 13th European conference on technology enhanced learning*.

Kandlhofer, M., Steinbauer, G., Hirschmugl-Gaisch, S., & Huber, P. (2016). Artificial intelligence and computer science in education: From kindergarten to university. In 2016 *IEEE frontiers in education conference (FIE)* (pp. 1—9). IEEE.

Kajiwara, Y., Matsuoka, A., & Shinbo, F. (2023). Machine learning role playing game: Instructional design of AI education for age-appropriate in K-12 and beyond. *Computers and Education: Artificial Intelligence, 5*, 100162.

Karalekas, G., Vologiannidis, S., & Kalomiros, J. (2023). Teaching machine learning in K-12 using robotics. *Education Sciences, 13*(1), 67.

*Kaspersen, M. H., Bilstrup, K. E. K., Van Mechelen, M., Hjorth, A., Bouvin, N. O., & Petersen, M. G. (2021, June). VotestratesML: A high school learning tool for exploring machine learning and its societal implications. In *FabLearn Europe/MakeEd 2021—an international conference on computing, design and making in education* (pp. 1–10).

Keri, Z., & Elbatarny, H. S. (2021). The power of analogy-based learning in science. *HAPS Educator, 25*(1), 13–20.

*Kilhoffer, Z., Zhou, Z., Wang, F., Tamton, F., Huang, Y., Kim, P., Yeh, T., & Wang, Y. (2023, May). "How technical do you get? I'm an English teacher": Teaching and learning cybersecurity and AI ethics in high school. In *2023 IEEE symposium on security and privacy (SP)* (pp. 2032–2032). IEEE.

Kolb, A. Y., & Kolb, D. A. (2009). Experiential learning theory: A dynamic, holistic approach to management learning, education and development. In *The SAGE handbook of management learning, education and development* (Vol. 7, p. 42). SAGE.

Lai, C. L., & Hwang, G. J. (2015). High school teachers' perspectives on applying different mobile learning strategies to science courses: The national mobile learning program in Taiwan. *International Journal of Mobile Learning and Organisation, 9*(2), 124–145.

*Lee, I., Ali, S., Zhang, H., DiPaola, D., & Breazeal, C. (2021, March). Developing middle school students' AI literacy. In *Proceedings of the 52nd ACM technical symposium on computer science education* (pp. 191–197).

*Lee, S., Mott, B., Ottenbriet-Leftwich, A., Scribner, A., Taylor, S., Glazewski, K., Hmelo-Silver, C. E., & Lester, J. (2020, June). Designing a collaborative game-based learning environment for AI-infused inquiry learning in elementary school classrooms. In *Proceedings of the 2020 ACM conference on innovation and technology in computer science education* (p. 566).

Leitner, M., Greenwald, E., Wang, N., Montgomery, R., & Merchant, C. (2023). Designing game-based learning for high school artificial intelligence education. *International Journal of Artificial Intelligence in Education, 33*, 384–398.

*Li, K., & Song, S. (2019, June). Application of artificial intelligence in primary and secondary schools: A case study of scratch. In *International conference on applications and techniques in cyber security and intelligence* (pp. 2026–2030). Springer.

*Lin, P., Van Brummelen, J., Lukin, G., Williams, R., & Breazeal, C. (2020, April). Zhorai: Designing a conversational agent for children to explore machine learning concepts. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 34(9), pp. 13381–13388).

*Lin, P. Y., Chai, C. S., Jong, M. S. Y., Dai, Y., Guo, Y., & Qin, J. (2021). Modeling the structural relationship among primary students' motivation to learn artificial intelligence. *Computers and Education: Artificial Intelligence, 2*, 100006.

Long, D., & Magerko, B. (2020, April). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI conference on human factors in computing systems* (pp. 1–16).

*Lucas, J. M. (2009). K-6 outreach using "Computer science unplugged". *Journal of Computing Sciences in Colleges, 24*(6), 62–63.

Lye, S. Y., & Koh, J. H. L. (2014). Review on teaching and learning of computational thinking through programming: What is next for K-12? *Computers in Human Behavior, 41*, 51–61.

Mahon, J., Quille, K., Mac Namee, B., & Becker, B. A. (2022, March). A novel machine learning and artificial intelligence course for secondary school students. In *Proceedings of the 53rd ACM technical symposium on computer science education* (p. 1155).

*Mariescu-Istodor, R., & Jormanainen, I. (2019, November). Machine learning for high school students. In *Proceedings of the 19th Koli calling international conference on computing education research* (pp. 1–9).

Markham, T., Larmer, J., & Ravitz, J. (2003). Project based learning handbook: A guide to standards-focused project based learning for middle and high school teachers. Buck Institute for Education, Novato.

Marques, L. S., Gresse von Wangenheim, C., & Hauck, J. C. (2020). Teaching machine learning in school: *A systematic mapping of the state of the art*. *Informatics in Education, 19*(2), 283–321.

*Martins, R. M., von Wangenheim, C. G., Rauber, M. F., & Hauck, J. C. (2023). Machine learning for all!—introducing machine learning in middle and high school. *International Journal of Artificial Intelligence in Education*. https://doi.org/10.1007/s40593-022-00325-y.

McCarthy, J. (2004). What is artificial intelligence? *Engineering Materials and Design, 32*(3), 1–14.

McMillan, J. H., & Schumacher, S. (2010). *Research in education: Evidence-based inquiry*. Pearson.

*Melsión, G. I., Torre, I., Vidal, E., & Leite, I. (2021, June). Using explainability to help children understand gender bias in AI. In *Proceedings of the interaction design and children*, Athens, Greece (pp. 87–99).

Miao, F., Holmes, W., Huang, R., & Zhang, H. (2021). *AI and education: A guidance for policymakers*. UNESCO Publishing.

Miao, F., & Shiohira, K. (2022). *K-12 AI curricula*. UNESCO Publishing.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & Prisma Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Medicine, 6*(7), e1000097.

*Ng, D. T. K., & Chu, S. K. W. (2021). Motivating students to learn AI through social networking sites: A case study in Hong Kong. *Online Learning, 25*(1), 195–208.

Ng, D. T. K., Leung, J. K. L., Su, M. J., Yim, I. H. Y., Qiao, M. S., & Chu, S. K. W. (2023). *AI literacy in K-16 classrooms*. Springer.

*Ng, D. T. K., Luo, W. Y., Chan, H. M. Y., & Chu, S. K. W. (2022). An examination on primary students' development in AI Literacy through digital story writing. *Computers and Education: Artificial Intelligence 3,* 100054.

*Norouzi, N., Chaturvedi, S., & Rutledge, M. (2020, April). Lessons learned from teaching machine learning and natural language processing to high school students. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 34(9), pp. 13397–13403).

Papert, S., & Solomon, C. (1971). Twenty things to do with a computer. In S. Papert, C. Solomon, E. Soloway, & J. C. Spohrer (Eds.), *Studying the novice programmer* (pp. 3–28). Lawrence Erlbaum Associates.

Park, Y., & Shin, Y. (2021). Tooee: A novel scratch extension for K-12 big data and artificial intelligence education using text-based visual blocks. *IEEE Access, 9*, 149630–149646.

Pedaste, M., Mäeots, M., Siiman, L. A., De Jong, T., Van Riesen, S. A., Kamp, E. T., Manoli, C. C., Zacharia, Z. C., & Tsourlidaki, E. (2015). Phases of inquiry-based learning: Definitions and the inquiry cycle. *Educational Research Review, 14*, 47–61.

Pedro, F., Subosa, M., Rivas, A., & Valverde, P. (2019). Artificial intelligence in education: Challenges and opportunities for sustainable development. Roscongress Building Trust.

*Perach, S., & Alexandron, G. (2022, June). A blended-learning program for implementing a rigorous machine-learning curriculum in high-schools. In *Proceedings of the 9th ACM conference on learning@ Scale* (pp. 267–270).

Piaget, J. (2000). Piaget's theory of cognitive development. In *Childhood cognitive development: The essential readings* (Vol. 2, pp. 33–47). Blackwell.

Priya, S., Bhadra, S., Chimalakonda, S., & Venigalla, A. S. M. (2022). ML-Quest: A game for introducing machine learning concepts to K-12 students. *Interactive Learning Environments. DOI, 10*(1080/10494820), 2022.

Qin, J. J., Ma, F. G., & Guo, Y. M. (2019). Foundations of artificial intelligence for primary school.

Resnick, M., Myers, B., Nakakoji, K., Shneiderman, B., Pausch, R., Selker, T., & Eisenberg, M. (2005). Design principles for tools to support creative thinking. In *Creativity support tools: Report from a US national science foundation sponsored workshop*.

Rina, R., Kluzer, S., & Punie, Y. (2022). *DigComp 2.2: The Digital competence framework for citizens-with new examples of knowledge, skills and attitudes* (No. JRC128415). Joint Research Centre (Seville site).

Rizvi, S., Waite, J., & Sentance, S. (2023). Artificial Intelligence teaching and learning in K-12 from 2019 to 2022: A systematic literature review. *Computers and Education: Artificial Intelligence, 4*, 100145.

*Rodríguez-García, J. D., Moreno-León, J., Román-González, M., & Robles, G. (2020, October). Introducing artificial intelligence fundamentals with LearningML: Artificial intelligence made easy. In *8th International conference on technological ecosystems for enhancing multiculturality* (pp. 18–20).

*Rodríguez-García, J. D., Moreno-León, J., Román-González, M., & Robles, G. (2021, March). Evaluation of an online intervention to teach artificial intelligence with LearningML to 10–16-year-old students. In *Proceedings of the 52nd ACM technical symposium on computer science education* (pp. 177–183).

*Sabuncuoglu, A. (2020, June). Designing one year curriculum to teach artificial intelligence for middle school. In *Proceedings of the 2020 ACM conference on innovation and technology in computer science education* (pp. 96–102).

*Sakulkueakulsuk, B., Witoon, S., Ngarmkajornwiwat, P., Pataranutaporn, P., Surareungchai, W., Pataranutaporn, P., & Subsoontorn, P. (2018, December). Kids making AI: Integrating machine learning, gamification, and social context in STEM education. *In 2018 IEEE international conference on teaching, assessment, and learning for engineering (TALE)* (pp. 1005–1010). IEEE.

Sanusi, I. T., & Oyelere, S. S. (2020). Pedagogies of machine learning in K-12 context. In 2020 *IEEE frontiers in education conference (FIE)* (pp. 1–8). IEEE.

Sayers, A. (2008). Tips and tricks in performing a systematic review. *British Journal of General Practice, 58*(547), 136–136.

*Scherz, Z., & Haberman, B. (1995, March). Logic programming based curriculum for high school students: The use of abstract data types. In *Proceedings of the 26th SIGCSE technical symposium on computer science education* (pp. 331–335).

Sestino, A., & De Mauro, A. (2022). Leveraging artificial intelligence in business: Implications, applications and methods. *Technology Analysis & Strategic Management, 34*(1), 16–29.

*Shamir, G., & Levin, I. (2021). Neural network construction practices in elementary school. *KI-Künstliche Intelligenz, 35*(2), 181–189.

*Shamir, G., & Levin, I. (2022). Teaching machine learning in elementary school. *International Journal of Child–Computer Interaction, 31*, 100415.

Smerdon, B. A., Burkam, D. T., & Lee, V. E. (1999). Access to constructivist and didactic teaching: Who gets it? Where is it practiced? *Teachers College Record, 101*(1), 5–34.

Smith, B. L., & MacGregor, J. T. (1992). What is collaborative learning. In *Collaborative learning: A sourcebook for higher education*. National Center on Postsecondary Teaching, Learning, and Assessment Publishing, Pennsylvania State University.

Su, J., & Yang, W. (2022). Artificial intelligence in early childhood education: A scoping review. *Computers and Education: Artificial Intelligence, 3*, 100049.

Su, J., & Yang, W. (2023). AI literacy curriculum and its relation to children's perceptions of robots and attitudes towards engineering and science: An intervention study in early childhood education. *Journal of Computer Assisted Learning*. https://doi.org/10.1111/jcal.12867

Su, J., Zhong, Y., & Ng, D. T. K. (2022). A meta-review of literature on educational approaches for teaching AI at the K-12 levels in the Asia-Pacific region. *Computers and Education: Artificial Intelligence, 3*, 100065.

Su, J., Guo, K., Chen, X., & Chu, S. K. W. (2023). Teaching artificial intelligence in K–12 classrooms: a scoping review. *Interactive Learning Environments*, 1–20.

Su, J., Ng, D. T. K., & Chu, S. K. W. (2023). Artificial intelligence (AI) literacy in early childhood education: The challenges and opportunities. *Computers and Education: Artificial Intelligence, 4*, 100124.

*Toivonen, T., Jormanainen, I., Kahila, J., Tedre, M., Valtonen, T., & Vartiainen, H. (2020, July). Co-designing machine learning apps in K-12 with primary school children. In *2020 IEEE 20th International Conference on Advanced Learning Technologies (ICALT)* (pp. 308–310). IEEE.

Trybus, J. (2015). *Game-based learning: What it is, why it works, and where it's going* (p. 6). New Media Institute.

*Tseng, T., Murai, Y., Freed, N., Gelosi, D., Ta, T. D., & Kawahara, Y. (2021, June). PlushPal: Storytelling with interactive plush toys and machine learning. In *Proceedings of the interaction design and children* (pp. 236–245).

Tu, Y. F., & Hwang, G. J. (2020). Trends and research issues of mobile learning studies in hospitality, leisure, sport and tourism education: A review of academic publications from 2002 to 2017. *Interactive Learning Environments, 28*(4), 385–403.

Van Brummelen, J., Heng, T., & Tabunshchyk, V. (2021, May). Teaching tech to talk: K-12 conversational artificial intelligence literacy curriculum and development tools. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 35(17), pp. 15655–15663).

Vartiainen, H., Tedre, M., & Valtonen, T. (2020). Learning machine learning with very young children: Who is teaching whom?. International Journal of Child-Computer Interaction, 25*, 100182.

*Voulgari, I., Zammit, M., Stouraitis, E., Liapis, A., & Yannakakis, G. (2021, June). Learn to machine learn: designing a game based approach for teaching machine learning to primary and secondary education students. In *Proceedings of the interaction design and children* (pp. 593–598).

*Wan, X., Zhou, X., Ye, Z., Mortensen, C. K., & Bai, Z. (2020, June). SmileyCluster: Supporting accessible machine learning in K-12 scientific discovery. In *Proceedings of the interaction design and children conference* (pp. 23–35).

Wang, T., & Cheng, E. C. K. (2021). An investigation of barriers to Hong Kong K-12 schools incorporating Artificial Intelligence in education. *Computers and Education: Artificial Intelligence, 2*, 100031.

Wegerif, R. (2007). *Dialogic education and technology: Expanding the space of learning* (Vol. 7). Springer, London.

Wegerif, R. (2011). Towards a dialogic theory of how children learn to think. *Thinking Skills and Creativity, 6*(3), 179–190.

*Williams, R., Park, H. W., & Breazeal, C. (2019b). A is for artificial intelligence: The impact of artificial intelligence activities on young children's perceptions of robots. In *Proceedings of the 2019 CHI conference on human factors in computing systems*.

*Williams, R., Park, H. W., Oh, L., & Breazeal, C. (2019a, July). Popbots: Designing an artificial intelligence curriculum for early childhood education. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 33(1), pp. 9729–9736).

Wong, K.-C. (2020). Computational thinking and artificial intelligence education: A balanced approach using both classical AI and modern AI. In: *Proceedings of international conference on computational thinking education 2020* (p. 108), The Education University of Hong Kong.

Yim, I. H. Y. (2023). Design of Artificial Intelligence (AI) education for primary schools: Arts-based approach (pp. 65–90). ISTES BOOKS.

*Yoder, S., Tatar, C., Aderemi, I., Boorugu, S., Jiang, S., & Akram, B. (2020). Gaining insight into effective teaching of AI problem-solving through CSEDM: A case study. In *5th Workshop on computer science educational data mining*.

Zhou, X., Van Brummelen, J., & Lin, P. (2020). Designing AI learning experiences for K-12: Emerging works, future opportunities and a design framework. arXiv preprint. arXiv:2009.10228.

Iris Heung Yue Yim is a Ph.D student in the Faculty of Education at the University of Cambridge. Her research interests include Artificial Intelligence literacy, dialogic education, STEM + Arts education, arts-based pedagogy, technological enhanced pedagogic innovation, early childhood and primary education.

Jiahong Su is a Ph.D. candidate in the Faculty of Education at the University of Hong Kong. Her research focuses on AI in early childhood education, computational thinking, and AI literacy. Her recent publications have appeared in international peer-reviewed journals such as *Computers & Education, British Journal of Educational Technology, and Educational Technology Research and Development*.