

Bring the Intelligent Tutoring Robots to Education: A Systematic Literature Review

Xinyue Zhang, Fangqing Zhu, Kun Wang, Guitao Cao, Yaofeng Xue, Mingzhuo Liu

Abstract—Advances in artificial intelligence technologies have given rise to traditional robotics. Intelligent tutoring robots, supported by artificial intelligence technologies and hardware design, have sparked a new revolution in all walks of traditional education. Despite the growing number of research papers published on intelligent tutoring robots, and a few limited reviews focusing on specific technologies or theoretical aspects, there is still no wide-ranging review work that systematically summarizes the studies from the perspectives of theoretical level and practical implications concluded in experiments. To address this challenge and promote a common understanding of the concept of intelligent tutoring robot, we conducted a systematic literature review of papers published between 2016 and 2023. We investigated the construction of intelligent tutoring robots, the advanced artificial intelligence technologies employed, and intelligent tutoring robots' applications in educational contexts. From a total of 1751 publications, we selected and analyzed 105 main studies to identify and address three research questions: 1) How does the construction of intelligent tutoring robots affect education? 2) What artificial intelligence technologies enable intelligent tutoring robots to be “intelligent”? 3) How are intelligent tutoring robots applied in educational contexts? Additionally, we discuss the challenges of current research and provide an outlook on future development trends to provide guidelines for participants and researchers in the fields of intelligent tutoring robots.

Index Terms—Intelligent Tutoring Robots, Artificial Intelligence in Education, Systematic Literature Review, Instructional Tools, Autonomous Tutors, Educational Contexts.

I. INTRODUCTION

IN recent years, the steady development of educational technology has provided new opportunities for teaching and learning while responding to new educational needs. For the sake of the popularization of artificial intelligence (AI) technology, the field of education has evolved enormously. The combination of AI and education leads to a multidisciplinary field, which is Artificial Intelligence in Education (AIED).

Manuscript created October, 2023; This work was supported by the National Nature Science Foundation of China (61871186), the Open Project Program of Shanghai Engineering Research Center of Digital Education Equipment, East China Normal University (No. ERCDEE2021-01), and the Fundamental Research Funds. Xinyue Zhang also acknowledges the support of the China Scholarship Council program. (Corresponding author: Guitao Cao.)

Xinyue Zhang and Guitao Cao are with MoE Engineering Research Center of SW/HW Co-design Technology and Application, and are with Shanghai Institute of AI for Education, East China Normal University, Shanghai 200062, China (e-mail:xyzhang@stu.ecnu.edu.cn, gtcao@sei.ecnu.edu.cn).

Fangqing Zhu, Kun Wang, and Yaofeng Xue are with Shanghai Engineering Research Center of Digital Education Equipment, East China Normal University Shanghai 200062, China (e-mail:51214108053, 51214108026@stu.ecnu.edu.cn, yfxue@deit.ecnu.edu.cn)

Mingzhuo Liu is with School of Open Learning and Education, East China Normal University, Shanghai 200062, China (e-mail: lucy@dec.ecnu.edu.cn).

AIED has the potential to be the next effective add-on to traditional education [1]. With the vigorous development of AIED, the teaching and learning interaction mode of human-machine collaboration may become one of the main forms of education in the future [2], [3]. As one of the earliest visionaries to foresee the revolutionary impact of computers on education, Seymour Papert pioneered the creation of the first programming language designed specifically for children, known as Logo [4]. This programming manner, which employed the concept of “turtle graphics” [5], allowed children to engage in programming and project design, harnessing the power of computers to facilitate learning in mathematics, geometry, and the exploration of the microcosm while constructing their own cognitive frameworks. Papert's innovative work paved the way for technology integration in education. The early ideas of Papert and the theoretical underpinnings behind the development of the Logo language served as the foundation for various subsequent developments in children's programming tools and related research activities. Tools like Mindstorms [6], for example, were born under his influence. Papert played a pivotal role in introducing and advancing the concepts of educational robotics and computational thinking, laying the groundwork for the flourishing field of “educational robotics” in its traditional sense.

A. Intelligent Tutoring Robots in AIED

As an important part of AIED application, tutoring robots will be an invisible revolution, which communicates seamlessly in kinds of technologies [7], [8]. As times have moved on and technology has advanced, tutoring robots combined with AI technologies become a new type of tutor robot that is increasingly being researched in the educational domain, and highlight the introduction of intelligent interaction with external stimulus, which has led the focus of this systematic literature review work: **intelligent tutoring robots (ITRs)**. ITR typically refers to robots capable of assisting/being teachers in daily activities, including teaching, research, and professional development [9], [10], [11]. ITRs play multiple roles in education, such as tools to learn AI knowledge [12], [13], [14], and intelligent tutors [8]. However, it imposes very stringent constraints on ITR's definition. Based on Papert's theories and research, many educational tutoring systems have since improved upon the traditional educational robots, connecting some form of modular hardware structure with a related programming environment. For instance, the Fable modular robot system serves as a tool to learn AI creative learning facilitates anyone to build and program their own robots [15].

In scenarios where students collaborate to solve problems, they joyfully engage in learning. These scenarios require constructing a specific robotic entity, and programming this entity to accomplish specific tasks required by the scenario. In this way, students learn by constructing and developing a “reactive” robot. Can robots like these be classified as ITRs?

Mubin et al. [16] demonstrated that ITRs are passive when used as teaching aids, and their applicability to robotics education, where students will build, create, program, and reap the benefits. ITR can be a physical object (e.g., a robotics kit) that dictates an effective learning process and allows students to reflect on what they’ve learned as they go through this process of using the robotics kit, and how it can be applied to ongoing reality. Yuan et al. [17] contend that ITR is a specific instance within the realm of educational robots. ITR employs robots as the delivery platform, bearing various AI applications. This empowers ITRs to assume roles such as teaching assistants, mentors, and peer learners. The embedded AI applications have the capability to enhance and assist teachers in their instructional endeavors. With the continuous advancement and iteration of AI technology, researchers are focusing more on the role of robots as higher-order tutors [18], and such ITRs are not only intelligent teaching tools, but capable of playing the role of autonomous tutors.

Some scholars argue that ITRs do not refer to traditional reactive education robot systems/suites but rather to robots that exhibit higher intelligence skills, such as playing the role of a mentor or providing tutoring guidance. As an emerging field, there are several scholars proposed the relative definition of so far from a specific point of view. For instance, Zhu et al. [19] focus on interactions of ITRs with different age groups: “*A common need for primary school, adult and older age groups. For the primary school group, ITRs help reduce the workload of teachers and provide remedial instruction. For the adult population, ITRs provide personalized instruction and reduce or eliminate commuting time to classes. Additionally, ITRs take on the role of a teacher or peer, patiently helping older adults who are slower in learning speed, memory, and reaction time through repetitive practice, especially in learning computer skills*”. Considering that current research has focused more on the functional realization of robots than on the human-robot relationship, Zhang et al. [20] combined previous research findings and argued that “*based on human intelligence and machine intelligence, ITRs are educational service robots that collaborate with human teachers in teaching, organization, implementation, and management to improve educational performance in an intelligent educational environment. As pedagogues, ITRs aim to empower, enable and augment human teachers, optimize teaching structures, build new teacher-student relationships, and cultivate learners and educators in an intelligent era*”.

All of the above definitions reflect the researcher’s insight and opinion from different perspectives. However, there is currently no widely accepted, standard definition for introducing “intelligent tutoring robots”. Based on previous definitions, we consider ITR as a specific instance of ITS, constructed using real or simulated robots, serving as personalized learning tools for students. On a micro-level, ITRs

are typically classified into ***Instructional tools-Autonomous tutors framework***. The first part is instructional tools that adhere to the Papert framework, using hardware elements as a medium to imbue ITRs with capabilities such as knowledge tracing, affective computing, and intelligent Q & A (ethical issues related to these technologies are assumed to be in compliance and will not be further discussed in this paper), etc. Under the guidance of teachers, these ITRs are employed to address students’ needs, enhancing their self-confidence and learning abilities while “constructing” their own self-awareness frameworks and seamlessly integrating technology into the learning process. Under the guidance of teachers, these ITRs can be used to address students’ requirements, enhance students’ self-confidence and learning abilities, construct self-awareness frameworks, and integrate technology into learning. The second part represents the ideal form of ITRs, presented in the most advanced robot forms of the intelligent era. These robots embed AI algorithm models capable of integrating high-quality resources, extensively modeling every specific educational scenario through data analysis, and possessing adaptability, prediction, and proactive capabilities.

B. Literature Review

Despite increasing scholarly interest in ITRs, there remains a notable scarcity of comprehensive reviews in this field. Most existing literature tends to focus on specific applications of tutor robots, such as the work by Van den Berghe et al. [21], which highlights achievements in Robot-Assisted Language Learning (RALL) and explores the use of social robots in language education. Similarly, Lin et al. [22] have provided valuable insights from 22 empirical studies on how educational robots can foster oral interactions in language classrooms, showcasing the potential of robots to assume roles traditionally held by human teachers. Rosanda et al. [23] reviewed the deployment of tutor robots in educational settings beyond Robotics subjects, focusing on anthropomorphic robots that engage actively in classrooms, stressing tutoring robots’ roles in education. While these contributions are significant, they often overlook the broader integration of AI technology with ITRs. Other reviews have explored the education robots or social robots’ development in education. Cayetano-Jiménez et al. [24] reviewed the educational use of soft robots in robotics, highlighting their benefits over rigid robots for expanding design and material topics. Mangina et al. [25] provided an overview of educational robotics in primary and preschool education. Johal et al. [26] summarized the current research directions and potential gaps in the study of social robots within the educational field. Woo et al. [27] investigated 23 studies conducted between 2000 and 2020 that examined social robots in classroom environments. Whereas, they seldom place tutor robots at the center of their analysis. Recognizing the transformative impact of AI on tutoring robots, some scholars have embarked on more focused inquiries. Woolf’s early exploration of AI technologies in ITRs [28] and Yang et al.’s analysis of ITR architecture [29] represent steps toward bridging the gap between education and robotics. However, these examinations miss out on the latest advancements in

robot technology and AI, without fully articulating how AI technologies confer “intelligence” upon tutoring robots from both developmental and operational perspectives. Hence, a systematic literature review on ITRs should be investigated to better comprehend the characteristics of ITRs and the corresponding AI technologies they adopt as well as the educational contexts in which they have applied.

To better explore and understand the above aspects, we review the valuable journal articles and conference papers relating to ITRs on the basis of reading and analyzing the pertinent literature in recent years from 2016 to 2023. We chose 2016 as the starting point for our literature collection for several reasons. First, 2016 marked a key period in the advancement of artificial intelligence and machine learning technologies. Significant progress in areas such as deep learning, natural language processing, and robotic perception provided valuable data and case studies for the development of ITRs. Second, over the past decade, educational technology has undergone significant transformation, especially in personalized learning and remote education. Starting from 2016 allows us to capture the impact of this transformation on the research and application of intelligent tutoring robots. Third, there have been notable changes in the global educational environment, such as the widespread adoption of remote education and the diversification of learning methods. A literature review starting from 2016 focuses more on the latest technological advancements and educational trends, while minimizing the need to deal with outdated or irrelevant information.

Employing predetermined criteria such as publication years and research methods, we screened the gathered literature to identify materials suitable for inclusion in our review. Specifically, we pick 105 main studies out of a total of 1,751 studies. Thoroughly examining the selected literature, we scrutinized the aims, methods, results, and conclusions of each study. Subsequently, we systematized and analyzed the acquired information. As a result of this comprehensive process, we derived three distinct research questions that emerged from our meticulous reading and analysis:

- 1) How does the construction of ITRs affect education?
- 2) What AI technologies enable ITRs to be “intelligent”?
- 3) How are ITRs applied in educational contexts?

Based on the exploration of three core research questions, we investigate the convergence perspective of ITRs, and summarize the characteristics of ITRs with the aim of providing consistency in the term ITRs for future research in this field.

II. RESEARCH METHOD

We focus on evaluating current research landscape of ITRs, highlighting notable achievements, and projecting future research trajectories. As shown in Figure 1, we follow Kitchenham and Charters’ systematic review methodology [30].

A. Research Questions

ITRs represent an emerging technology, and understanding how they specifically transform teaching methods, learning efficiency, and the educational experience is crucial. Hence, this paper constructs a comprehensive analytical framework for

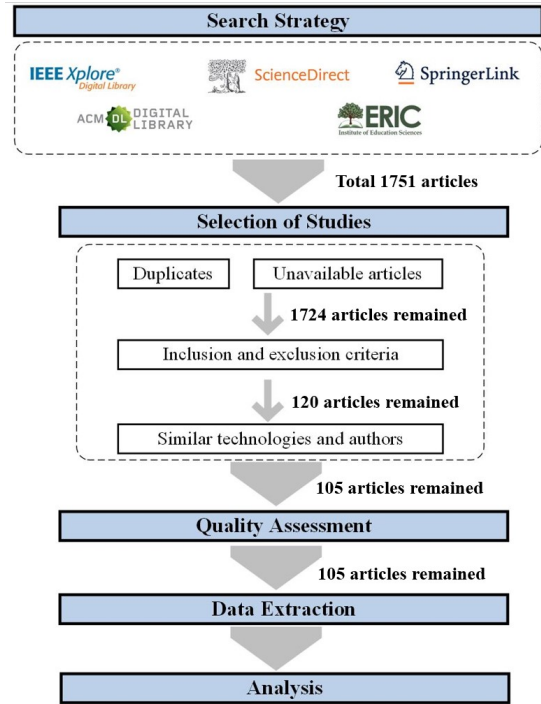


Fig. 1. Illustration of review method.

ITRs, from their technological construction to their practical application. Our research questions are as follows:

1) *Research Question 1 (RQ1). How does the construction of ITRs affect education?*: RQ1 helps understand the respective advantages and disadvantages of ITRs in different forms, such as real robots and simulated robots. Furthermore, through the study of ITRs’ structures, sensors, power systems, etc., new technological applications and improvements can be explored to enhance the performance and functionality of robots and further promote the development of this field. Moreover, it is possible to explore the preferences and requirements of educational users. Different users may have different preferences for the appearance, size, and materials of ITRs, thus understanding the physical construction of robots can help design products that meet user expectations.

2) *Research Question 2 (RQ2). What AI technologies enable ITRs to be “intelligent”?*: The AI technologies have developed by leaps and bounds, which would promote the development of AI for education through the integration of AI technologies and ITRs. And RQ2 spots the intelligence dedicated to ITRs.

3) *Research Question 3 (RQ3). How are ITRs applied in educational contexts?*: RQ2 focuses on the specific AI technologies used in ITRs, and RQ3 explores the widespread application and effectiveness of existing ITRs in educational contexts.

B. Database and Search Terms

To gather as many papers as possible, five major databases were searched: 1) IEEE Xplore; 2) Science Direct; 3) Springer Link; 4) ACM Digital Library; and 5) ERIC (Educational Resources Information Center). Preprints and scientific reports

were eliminated, and only papers in journals and conference proceedings are chosen.

Initially, search terms like “tutoring” and “robot” were keyed in but in order to narrow down the result, we used a similar approach to what Toh et al. [31] employed. Therefore, the following query string was searched: (((‘intelligent’ OR ‘AI’ OR ‘Artificial Intelligence’) AND ‘tutor’ OR ‘tutoring’) AND ‘robots’ OR ‘robotic’). Articles reviewed were limited to those published from 2016-2023.

TABLE I
INCLUSION AND EXCLUSION CRITERIA OF SELECTION PROCESS.

Inclusion Criteria	Exclusion Criteria
(a) Publication year between 2016-2023.	(a) Preprints, scientific reports, or extended abstract, etc.
(b) Peer-review journal articles or conference articles in English.	(b) Articles in other languages, such as Chinese, French, etc.
(c) Apply in educational scenarios.	(c) Despite citing the term “tutoring robots”, the robot is not developed for educational applications.
(d) Act as instructional tools or autonomous tutors in education.	(d) Citing the term “tutoring robots”, but dealing with the life assistance of the old and young alike.
(e) and AI technologies are involved in the technological component.	(e) Did not mention or deeply analyze the application from theoretical or empirical aspects in education.

1,751 studies remained after the initial search, with 54 articles from IEEE Xplore, 505 articles from Science Direct, 708 articles from Springer Link, 478 articles from ACM Digital Library, and 6 articles from ERIC. However, the initial search contains many impurities, such as duplicates and unavailable full-text studies. After removing 17 duplicates and 10 unavailable publications, 1,724 studies remained.

C. Inclusion and Exclusion Criteria

We applied the inclusion and exclusion criteria to eliminate articles unrelated to AI and tutoring robots based on the titles and abstracts, and select the most representative research as the main studies. We conducted a series of inclusion and exclusion criteria to obtain the final main studies, which is demonstrated in Table I. The inclusion criteria for our review are studies on ITRs applied in educational background, published in peer-reviewed international journals or conferences from 2016 to 2023. Articles not meeting these criteria are excluded. The specific inclusion and exclusion criteria are as follows:

1) The studies must have been published in peer-reviewed journals or conferences since 2016 to ensure novelty and quality. They must be published in English-language international journals or conferences to ensure wider reader accessibility for critique and analysis.

2) The selected studies should specifically concentrate on ITRs within the context of either K-12 or higher education. Studies that discuss AI-based robots or tutoring robots but do not demonstrate their application in educational settings are excluded.

3) The tutoring robots in the studies must act as instructional tools or autonomous tutors. Those not mentioning or lacking

in-depth analysis of advanced technology theory or its practical application in education are excluded.

Consequently, 105 publications remained.

D. Quality Assessment

It is hard to overstate the significance of the assessment of publications’ quality. The following 8 assessment criteria are adopted:

- *Quality assessment 1 (QA1)*: Is there an explicit explanation about the research targets?
- *Quality assessment 2 (QA2)*: Is there a sufficient description of the research background?
- *Quality assessment 3 (QA3)*: Is there a series of related work in the corresponding fields?
- *Quality assessment 4 (QA4)*: Is there a clear demonstration of the framework or architecture of ITRs’ technologies?
- *Quality assessment 5 (QA5)*: Is there a validation test for the technologies?
- *Quality assessment 6 (QA6)*: Are the results related to the initial research targets?
- *Quality assessment 7 (QA7)*: Is there a distinct statement about the research results?
- *Quality assessment 8 (QA8)*: Is there an outlook on future research trends?

Apart from 29 articles, such as Lopez-Rodriguez’s [32] and Balogh’s [33] work, that do not include perspectives on future work, the majority of studies meet the quality assessment. Since the absence of QA8 does not impact the research outcomes, these articles were not excluded from our work. After the process of quality assessment, all 105 publications remained.

E. Review and Coding Process

Concerning about 105 publications, three researchers reviewed the main studies to explore data inseparable from ITRs. The researchers read the full text and then finished the data extraction template. Table II demonstrates the template, which helps to clarify the structures and excavate solutions to research questions with respect to ITRs.

First, researchers categorized 105 main studies according to the following basic information: the title, abstract, type, authors, and targets of publications, as well as constructional strategies, adopted AI technologies, and applications in educational contexts.

Consequently, researchers extracted “construction” concepts from 105 main studies. The identification of “construction” includes two interventional divisions: 1) the construction process (such as how do the real robots [34], [35] or the simulated robots [36] are built), and 2) user preference about the ITRs’ construction. Therefore, researchers extracted “construction” concepts from the template according to the relative descriptions of authors (researchers can also add concepts that are not listed in the template).

As for “intelligent” concepts in main studies, researchers were concerned about the classification of AI technologies.

TABLE II
DATA EXTRACTION TEMPLATE.

Article Part	Review Content
<i>Basic Information:</i>	
Title	The title of articles.
Abstract	The abstract of articles.
Type	The publication type.
Authors	The authors' information.
Targets	The targets of the publication.
<i>RQ1: How does the construction of ITRs affect education?</i>	
Constructions	The construction strategies.
Preference of Users	The preference of educational users on different-constructional ITRs.
<i>RQ2: What AI technologies enable ITRs to be "intelligent"?</i>	
Knowledge Tracing	The detail of the AI algorithm.
Affective Computing	The detail of the AI algorithm.
Intelligent Q&A	The detail of the AI algorithm.
<i>RQ3: How are ITRs applied in educational contexts?</i>	
Applications	Choose the type: Teachers (subject education), Tools to learn (tutoring support)
Teachers (subject education)	Choose the application scenarios: general courses, STEM education (preschool education, primary and secondary education, and university education.), practical skills (social skills, hands-on skills, physical skills, language ability, and cognition ability), tutor after class, special education.
Tools to learn (tutoring support)	Choose the application scenarios: learning companion, learn-through-play ITR.

However, as a multidisciplinary area, there are inadequate advanced AI technologies designed for ITRs. Therefore, the template previously offers three common and novel AI technologies. By the same token, researchers can introduce other AI technologies.

With regard to the "application" part, the review process focused on the scenarios of ITRs applying in. Since the applications of ITR is inextricably intertwined with introducing intelligence in education, researchers reviewed the main studies by summarizing the roles of ITRs and classifying publications according to role characteristics, i.e. they play the role as teachers or teaching aids.

F. Analysis of The Publications Included in ITRs

Figure 2 depicts the publication type distribution per year of 105 main studies. Of the 105 publications selected, 49 articles (46.67%) were from conference proceedings, and 56 articles (53.33%) were published in journals. Regarding the number of articles selected, the conference with the highest number of selected articles is *ACM IEEE International Conference on Human Robot Interaction*, with 4 articles. And the journals with the highest number of selected studies are *Advances in Intelligent Systems and Computing*, and *Journal of Intelligent Robotics Systems*, with 5, and 4 articles, respectively.

The 105 publications are written by 405 authors from 40 countries/regions. Among the 405 authors, 28 authors participated in more than two studies. Francisco Bellas has the highest number of contributing studies, with 5 articles [7],

[37], [12], [38], [39], followed by Abraham Prieto, with 4 articles [37], [12], [38], [39]. Among the 44 countries/regions, the USA is the most relevant country (with 24 articles), followed by China (with 15 articles) and Spain (with 12 articles). Exploring the number of research areas, the most relevant area is computer science, with 56 articles, followed by education educational research, with 31 articles.

III. RESULTS

A. RQ1: How does the construction of ITRs affect education?

As intelligent robotic products, ITRs have their own characteristics. ITRs in the form of instructional tools facilitate learners to incorporate technology into their learning by constructing robots. Papert underscores the idea that children should "Learn by Making" [40], focusing on the "process" of knowledge acquisition. He advocates that children should transform their mental ideas into concrete forms using specific technological mediums, acquiring knowledge through design and creation. In essence, knowledge is not acquired through the transmission of information from instructors. Instead, children should become the "constructors" of their own intellects. Moreover, when learners actively utilize tangible tools to design and create in the real world, the knowledge they gain becomes the most meaningful. ITRs with higher-level intelligence can capture the learners' attention with their unique appearance. Their physical and social presence benefits the learners' educational experience [41]. In this section, we explore the constructional science of ITRs in terms of construction based on the selected main literature (see Table III).

1) Constructing ITRs that facilitate teaching activities:

Many researchers have built up ITRs from scratch, bringing improvement into various aspects of educational scenarios. Hashan et al. [42] described in detail how a three-axis drawing robot was designed from scratch and implemented for educational teaching purposes. This robotic system can be used as a tool to help university students understand numerical control computer and computer-aided design skills. Using a combination of applied science theory and practice, Lopez-Rodriguez et al. [32] designed an educational robot called Andruino-R2, which is development based on Arduino and Android. Andruino-R2 enables the use of a variety of sensors



Fig. 2. The number of publication types per year of selected 105 main studies.

(e.g. light sensors, ultrasonic sensors) and various communication resources. The construction of Andruino-R2, together with its programming, provides the educational field with learning outcomes and resources in different directions, especially in the areas of intelligent automatic control and computer vision. Sáenz Zamarrón et al. [43] introduced the design and construction of the robotic arm in 4 degrees of freedom, which provided a platform for students in various practical studies. Hu et al. [44] built ITRs based on robotic process automation (RPA) robots, and provided online students with automated intelligent responses. For kernel construction, authors embedded algorithms, such as natural language processing, machine learning, knowledge representation, reasoning, massively parallel computing, and rapid domain adaptation in ITRs. RPA-based ITRs iteratively analyzed user processes by observing students in their studies. The results of the study showed that students achieved higher grade point averages with the help of RPA-based ITRs.

Furthermore, some researchers consider cost-cutting to attract the attention of ITRs' users. Vandevelde et al. [45] created a low-cost do-it-yourself construction system for small robots in the educational scenario. The authors designed three construction systems and a preference showed that this work represented a solid first step toward an inexpensive, "hackable" construction system for educational robotics. López-Rodríguez et al. [46] designed an open low-cost modular and extendable mobile educational robot with Local Area Network and Internet connection capabilities, employment in educational scenarios, such as information and engineering classrooms and labs, as well as open online courses. Hayosh et al. [47] gave up 3D printing instead of constructing a low-cost 2D-based plywood robot to support the functions during students' learning process, such as face tracking and facial emotion recognition. Balogh et al. [33] presented a modular and customizable construction kit for building mobile robotic platforms with various controller boards guided by open-design principles to create functional and ready-to-use construction of the educational robot, and the whole process of producing is achieved by low-cost 3D printing technology.

2) *Educating users on their preferences for ITRs construction*: Many scholars focus on ITRs with different appearance patterns that will cause different results in the process of teaching has become a hit of concern [54]. Björling et al. [51] conducted an exploratory study with 24 Spanish-speaking English language learners. The results of this participatory design approach showed that students, discussing under the leadership of the educational robots, were interested in the robots, but hesitant to communicate with the robot since

the social robot's appearance and behavior made them feel uncomfortable. The result showed that the outward appearance of intelligent educational robots could affect learners' psychological perceptions. Velentza et al. [53] compared the opinions about the ideal characteristics (including appearance) of ITRs from the perspectives of pre-service teachers, when they are actually taught by an educational robot and a real human tutor, the result of which showed that teachers as educational robots' future users should interact more with educational robots performing the target task, to be able to accurately select the target robot appearance, to improve the teaching performance. Reich-Stiebert et al. [48] involved users in design decisions throughout to investigate the requirements and preferences of the target group for educational robot design. They investigated and analyzed the design preferences of educational robots among 116 college students, concluding that college students prefer medium-sized robots with human characteristics, while preferring robots with minimal facial features. Likewise, Christodoulou et al. [49] stressed the importance of humanoid appearance and the integration of various social cues for the design of robots in educational scenarios. Li et al. [50] assessed emotional impressions of the appearance of humanoid robots, recorded through a combination of eye-tracking and EEG signals. One of the results showed that people paid the most attention to the head of the humanoid robot's appearance, the second most attention was drawn to the torso, the third most attention was drawn to the robot's legs and hands, and people paid less attention to the robot's arms and feet. However, Klüber et al. [52] argued that anthropomorphic appearance is not everything. The authors conducted an online survey and found that human-like-looking robots can be more approachable and perceptive to people, yet that consideration of robot attributes should not be taken in isolation. Klüber demonstrated that overall consideration of interaction factors should always be the goal of the design.

What is more, ITRs in the form of robotic platforms are also universally popular among educational users, yet not in the shape of a robot in the traditional sense. For instance, Robobo ITR consists of a variety of sensors and essential hardware devices such as cameras, microphones, speakers, tactile screens, and other components that enable running AI-related algorithms of computer vision, speech recognition, human-robot interaction, and remote control [12], [39]. Based on the Robobo educational robot, Bellas et al. [38] proposed a specific curriculum for the introduction of next-generation educational robotics in high schools. Such a smartphone-based platform has already been successful in more than 10 different countries. Guerreiro-Santalla et al. [7] leveraged Robobo ITR to provide a structured lecture activity for high school teachers to introduce high school students to the basics in the scope of AI. Students showed positive attitudes and receptiveness when using Robobo ITRs for learning purposes.

TABLE III
CONSTRUCTION OF ITRs.

Construction	Frequency	References
Constructing ITRs that facilitate teaching activities	8	[42], [47], [32], [43], [45], [46], [33], [44]
Educating users on their preferences for ITRs construction	11	[48], [49], [50], [51], [52], [53], [54], [38], [7], [12], [39]

B. RQ2: What AI technologies enable ITRs to be "intelligent"?

In this section, we focus on three potential AI technologies according to main studies: 1) Knowledge Tracing, 2) Affective

Computing, and 3) Intelligent Q&A. Table IV shows a brief overview of the relevant publications.

1) *Knowledge Tracing*: Knowledge tracking is based on modeling student behavior sequences to predict students' mastery of knowledge. Knowledge tracing is the core and key to constructing an adaptive education system [55], [56].

Early knowledge-tracing models all relied on traditional models, such as first-order Markov models. For example, the Bayesian knowledge tracing [57], [58]. The introduction of deep learning into knowledge tracing first appeared in a paper Deep Knowledge Tracing (DKT) by Piech et al [59]. The authors proposed the concept of using deep knowledge tracing to model students' learning, and the core network is based on recurrent neural networks. There are some advantages to introducing deep learning into the knowledge tracing field [59]. Due to the rapid development of deep learning, researchers provide more mature knowledge tracking technology to model students' mastery of existing knowledge. For example, Shen et al. [60] designed a new DKT paradigm and model to model students' learning process and monitor their knowledge state. The whole model consists of three parts, including the learning module, forgetting module, and predicting module. The learning module focuses on the knowledge status relevant to the current knowledge points, combining with current learning benefits and intervals obtained by forgetting module, predict the performance of students with the predicting module.

In real-world educational practice, through the introduction of knowledge tracing and knowledge representation in the field of education, the online teaching system has become an intelligent teaching system (ITS), which is different from the previous Massive Open Online Courses (MOOCs) courses. For example, ITS personalizes various and effective learning paths for each student, which tailors their learning experience based on their own requirements and proficiency levels. David et al. [61] introduced a new algorithm in ITS for sequencing questions to students, focusing on personalizing educational content to their individual needs. Using a Bayesian knowledge tracing model that accounts for partial credit scores, multiple attempts, and item difficulty, the algorithm has been empirically shown to enhance performance and engagement in real school settings compared to a baseline method. Implemented in two different school classes and compared with a baseline algorithm designed by pedagogical experts, the Bayesian knowledge tracing sequencing approach led students to solve more challenging questions and achieve higher performance. Additionally, students exhibited greater engagement, as evidenced by increased interaction time, log-ins, and positive feedback. The approach demonstrates significant potential in designing personalized educational methods that effectively meet individual learning needs. In contrast, MOOCs typically offer the same course content to all students, lacking personalized guidance. Furthermore, ITS can monitor students' learning progress and adjust the learning path based on their performance. Conversely, MOOCs usually provide course materials but do not offer personalized management of learning progress. Moreover, ITS typically exhibits a higher level of interactivity, allowing for real-time conversations with students, answering questions, and explaining concepts. MOOCs

TABLE IV
AI TECHNOLOGIES IN ITRS.

AI technologies	Frequency	References
Knowledge Tracing	10	[55], [56], [60], [61], [62], [63], [64], [65], [66], [67]
Affective Computing	15	[68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], [82]
Intelligent Q&A	9	[83], [84], [85], [86], [87], [88], [89], [90], [91]

primarily rely on videos and text materials, which limit their interactivity. In summary, ITS, by employing knowledge tracking technology, provides a more personalized, interactive, and adaptive learning experience, while MOOCs generally offer standardized course content with limited personalized guidance and interactivity. Minn et al. [62] proposed a deep knowledge tracing model to evaluate students learning ability and further predict students' study performance, which tended to trace students' knowledge states during learning and offered students appropriate supportive learning instructions. However, the above method ignored the individualization of students, hence, Shen et al. [63] paid attention to students' continuous learning interactions and extract individualized learning rates to further assist students to learn knowledge concepts.

Furthermore, the introduction of knowledge tracing technology into ITRs can enrich the software construction of educational robots, providing users with more personalized services and promoting students' learning. Schodde et al. [64] developed an adaptive language ITR for child-robot interaction, employing knowledge tracing technology. This technology is based on a dynamic probabilistic model that connects a learner's skills, their observed behavior, and the tutoring actions of the system. When implemented in a robot language tutor, this technology effectively tracks the learner's progress. It informs the ITR about the next skill to teach and how to facilitate engaging, game-like interactions. The evaluation of this approach revealed that participants engaging with the adaptive ITR successfully acquired foreign language words, underscoring its practical effectiveness in educational settings. Sun et al. [65] maximized the learning gain of learners by selecting a specific task or a difficulty level. Liu et al. [66] leveraged the deep knowledge tracing method to provide personalized exercise recommendations by tracing students' learning states during the exercise. Ramachandran et al. [67] built intelligent robots with assistive tutors partially observable Markov decision process and trained the robots using data from a prior robot-student tutoring study, to provide personalized tutoring support over time for students.

2) *Affective Computing*: Affective computing is an umbrella term for human emotion, sentiment, and feelings [92]. General research shows that people are more inclined to have a robot that can feel their emotions and give appropriate feedback, which requires the robot to be able to carry out emotional calculations and emotional feedback.

Rhim et al. [68] found that when participants interact with positive robots, their favorability towards the robots can be increased. While Chita-Tegmark et al. [69] showed that hu-

mans are more inclined to choose robots with higher emotional intelligence. Fang et al. [70] showed that emotional expression has a positive impact on task allocation. In the following year, Yang et al. [71] proposed an emotional interaction robot and proved through experiments that it can serve people and improve the level of human mental health. Kaushik et al. [72] found that ITRs with affective computing skills can positively contribute to students' keeping alive sorting abilities.

The introduction of AI technology can help robots develop and improve in a more intelligent direction and provide better emotional computing services. On the basis of thermal-infrared-imaging computational psychophysiology, Spaulding et al. [74] introduced a novel affective extension to the Bayesian knowledge tracing model in ITRs, incorporating affective data for educational purposes. The data, derived from video records of children engaging in an interactive storytelling game with an ITR, are used to infer students' reading skills. The study found that children interacting with a tutoring robot, as opposed to a tablet, exhibited stronger engagement and enjoyment. Incorporating these affective signals in ITRs significantly enhanced the quality of knowledge inference models. The results indicate that affect-aware, physically embodied robot tutors offer more effective, empathetic educational experiences, highlighting the importance of integrating affect understanding with educational robots in learning environments. Filippini et al. [73] developed a novel affective computing approach using functional infrared thermal imaging to discern children's emotional states non-invasively, by analyzing facial temperature changes. This system, integrating cost-effective components, is embodied in a Computational Psychophysiological Module (CPM) that classifies emotional engagement into positive, neutral, and negative levels. Validated through a study with 17 children across 102 events, the CPM accurately identified children's interest levels in 71 cases. Misclassifications were mainly due to movement artifacts. This innovation marks a significant step in real-time emotional assessment in social robotics. Yadollahi et al. [75] grounded in Piaget's theory, aimed to develop a perspective-taking model for ITRs, tailored for educational settings. Currently poised for experimental application in an elementary school, the study will refine the model based on children's behavior, emotions, and perception in ITRs, enabling the ITRs to either adjust to or influence their perspectives in alignment with educational interaction goals. This ongoing research marks a significant step in advancing adaptive robotic technology in educational environments. Imbernón Cuadrado et al. [76] presented the development of affective ITRs for primary school children, emphasizing personalized support based on students' emotional states. It achieved 69.15% accuracy in identifying seven emotional states of children. Further user experience studies will compare different emotional models to assess the pedagogical effectiveness of the robot tutor. Kraus et al. [77] evaluated how ITRs can enhance learning by responding proactively to students' cognitive-affective states, such as frustration and confusion. Involving 40 students, the research found that while high levels of proactive behavior during negative states can reduce trust in the robot, they help maintain student focus. These findings suggest a nuanced

approach to proactive dialogue in robotic tutoring, balancing trust and concentration, and guide future enhancements in robotic tutoring systems. Gudi et al. [78] presented an Emotional Classification System (ECS), that enables the ITRs to proactively adapt to the students' mood, with a focus on a sign language tutor scenario for individuals with speech and hearing impairments. The effectiveness of ECS is demonstrated through real-time implementation on the Pepper robot, showcasing its potential to enhance educational interactions. Imbernón Cuadrado et al. [79] developed an environment integrating robot tutor with educational software to support primary school learning by identifying students' emotions and offering personalized support. It demonstrates a prototype using Scratch and NAO robots, proving the feasibility of non-intrusive emotion identification and a flexible architecture for diverse educational applications.

At the same time, the research results of Ippoliti et al. [80], Hirokawa et al. [81], and Muñoz et al. [82] showed that a good interactive process can promote the educational process. According to Dictionary.com [93], education is defined as the process of receiving or giving systematic instruction, and it encompasses a new public education system. Education is not limited to schools or colleges, nor is it restricted to a specific age group. Events that occur in our daily lives can also hold educational significance for us [94]. In the process of knowledge transmission and accompanying learning, if the educational robot can well capture the emotional changes of the educatees, it can provide timely appropriate services according to the emotional changes. Take the companion learning robot as an example. When an educated person is working on a difficult subject, he or she may show feelings such as depression and loss. At this point, ITRs can use the AI algorithm to capture and analyze the current mood and recommend easier questions later to boost confidence. Similarly, when the current question is relatively simple, the robot can slightly increase the difficulty of the later question. To conclude, we can follow the "jump to reach" principle to raise the child's upper limit.

3) *Intelligent Q&A*: The interaction between robots and human beings has gradually become the concentration of educational robot design. Besides, in the process of education, the language interaction between teachers and students or partners is a very important process, and the ITRs can use an AI algorithm to instantly understand the trainees' grasp of knowledge and thinking process at this moment according to the interaction process with the trainees. Besides, establishing a good interaction process between teachers and students can promote students' learning [95]. Therefore, whether the robots have a good intelligent question-answering system is also an important reflection of whether the ITRs are intelligent enough.

Ji et al. [84] investigated the potential Intelligent Q&A technologies embedded in ITRs, like chatbots, on online learning by surveying students and interviewing tutors in an online program. The findings suggest that ITRs with Intelligent Q&A skill could enhance the online learning experience for both students and tutors, but also highlight several concerns that need addressing for effective ITR integration in e-learning. More-

over, Hindriks et al. [85] designed a tutor robot for recognizing children's spoken responses to basic math problems, offering feedback on specific errors. Despite no observed learning improvements, findings highlight the robot's capability for autonomous interaction and the need for sophisticated algorithms to tailor feedback to children's performance. de Medeiros et al. [86] presented THOTH, a cognitive conversational agent developed to improve the teaching and learning experience using structured small talk in Q&A interactions. THOTH integrates twelve small talk segments to foster engaging and informal conversations during tutoring. A study in an Applied Artificial Intelligence course evaluated its effectiveness, focusing on interactivity and intentionality. The results indicate THOTH's potential as a beneficial tutoring tool, though it also identifies areas needing enhancement. He et al. [87] introduced an ITR that utilized an automated question-and-answer segment to engage the learners' thinking through voice interaction between learners and the robot for geometrical thinking training. It effectively engaged children and parents, enhancing learning exploration. Nguyen et al. [88] described a practical intelligent Q&A method for designing an ITR to assist Vietnamese high-school students in math, providing tips and automated problem-solving guidance, simulating real teacher-student interactions. Gunawan et al. [89] researched an Indonesian Q&A system for arithmetic word problems implemented on an intelligent humanoid robot, utilizing a pattern matching approach and natural language processing. The robot translates Indonesian speech to English text and tackles various linguistic challenges to provide solutions. Using the Natural Language Toolkit, the system achieves an accuracy of 80% to 100%, depending on the complexity of the problem, though the average response time is relatively slow at 1.12 minutes. Budiharto et al. [90] proposed a speech recognition system implemented in a humanoid robot for educational use in elementary schools, offering natural student interaction and face detection. With 73.3% recognition accuracy and 63.3% correct response rate, it shows improved performance over the NAO robot. Huang et al. [91] showcased an AI-powered educational robot designed to teach English vocabulary and engage in dialogues, boosting student engagement in primary school settings. It offers valuable insights for English teaching reform and represents a significant advancement in educational resource innovation and pedagogical methods. Guo et al. [83] built a robot designed for online learning, combining speech recognition and natural language processing to adaptively learn from user interactions, enhancing its tutoring capabilities. Implemented on humanoid robots Pepper and NAO, and Double Robotics' telepresence robot, it facilitates natural interaction and continuous learning without explicit programming.

C. RQ3: How are ITRs applied in educational contexts?

Notably, 52 out of the 105 publications answered this research question, where intelligence is shown in the form of the roles ITRs play. Studies involving ITRs' applications in education can be grouped into two main categories: 1) subject education, 2) tutoring/instructional support (see Table V). First, an ITR can be a teacher to leads students to learn

fresh subject knowledge. This knowledge includes general courses, as well as practical skills, and cognition ability. Second, an ITR can be tutoring/instructional support to assist with professional development for teachers, such as learning companion and learn-through-play tools.

1) *Intelligent Tutoring Robots in subject education:* (1) **General courses.** ITRs can play useful roles in delivering general knowledge to students. Llamas et al. [12] addressed two specific teaching units with the Robobo ITRs. Guerreiro-Santalla et al. [7] used Robobo ITR to provide a structured lecture activity for high school teachers on introducing high school students to the basics in the scope of AI. Students programmed on the Robobo ITR to design their own robotic pets, successfully providing students with an understanding of the fundamental concepts of natural interaction and the relevance of natural interaction to AI.

TABLE V
APPLICATIONS OF ITRs IN DIFFERENT EDUCATIONAL CONTEXTS.

Applications	Frequency	References
<i>Subject Education</i>		
General courses	2	[12], [7]
STEM education: in preschool education	8	[96], [97], [98], [99], [100], [101], [102], [103], [104], [105], [106], [107], [108], [109], [110], [101], [111], [112], [113], [114], [37]
STEM education: in primary and secondary education	13	[115], [116], [117], [118], [119]
STEM education: in university education	5	[120], [121]
Tutor after class	2	[122], [123]
Practical skills (Social skills)	2	[124], [125], [126], [127], [128], [129]
Practical skills (Hands-on skills)	6	[130]
Practical skills (Physical skills)	1	[21], [131], [132], [133], [134]
Practical skills (Language ability)	5	[135], [136]
Practical skills (Cognition ability)	2	[137], [138], [139]
Special education	3	
<i>Tutoring Support</i>		
Learning companion	2	[140], [141]
Learn-through-play	3	[142], [143], [144]

(2) **STEM education.** Besides, we explore and emphasize the applications of ITRs in STEM education [145]. STEM education builds a bridge in independent disciplines, providing students with an opportunity to know the world as a whole so that the fragmentary knowledge learned by students becomes interrelated [146], [147], [148].

Preschool education. The foundation of STEM education is preschool education [96]. Most preschool teachers, children, and parents are usually only familiar with the math and science components of STEM education [97]. Using robotics in education is an effective way to engage children in STEM learning in a developmentally appropriate way, where children can explore across disciplines through the use and production of technology [98]. As they explore, children learn interdisciplinary skills and knowledge, as well as mathematical concepts such as sorting, scientific inquiry, and problem-solving. Fridin et al. [149] found that when preschoolers learned about robotics,

their STEM-related skills improved significantly and were significantly higher than those of their peers, which means the application of STEM educational robots in preschool education is effective. Ching et al. [99] used the Keeko robot to help preschoolers develop computational thinking. The Keeko robot had a humanoid appearance and could be interacted with voice, screen, and programming. Research showed that preschool teachers were positive about the effects of Keeko robots on children's development. Sullivan et al. [100] implemented the KIBO robot course to cultivate the robot programming ability of 3- 6-year-old children. Students built robots of their choosing and designed their exteriors and interior programs to let them perform dances. The results showed that the children mastered new programming concepts during the task. Velentza et al. [150] assessed the effectiveness of programmable toys on children's cognitive domains of executive function (problem-solving, cognitive flexibility, and metacognition), visuospatial skills, and attention skills. The findings suggested that using the programmable toy may improve executive function, visual space, and attention in young children. Bursleson et al. [102] developed ALERT, a physics programming robot, to build physical programming environments for young children. Then, it was compared with Robopad, a virtual programming environment, to study the influence of different programming environments on children's STEM learning. It showed that the ALERT robot facilitated children's sequential programming to a greater extent, and it facilitated collaboration among children because it was not limited by a keyboard. García Terceño et al. [103] established a project called botSTEM. The overall goal of the project was to develop and analyze learning activities based on STEM educational robots, building a STEM teaching framework for teachers.

Primary and secondary education. STEM ITRs are widely used in primary and secondary schools, and related studies are various, including the development and application of STEM ITRs. Wongwatkit et al. [104] used AlphaBot, Waveshare's educational mobile robot suite, to develop a STEM project that allowed students to collaborate on a maze escape task. Students needed to analyze the maze, select and install the robot's components, and write instructions to help the robot out of the maze. Huang et al. [105] created STEM courses using Dash & Dot (Kid-oriented robots) and LEGO NXT (traditional industrial robots) to study the effects of different types of robots on students' performance and attitudes toward learning activities. The study showed that there was no significant difference between the two robots in students' grades and attitudes. Using Thymio, an educational robot, Carrillo-Zapata et al. [106] designed an educational workshop themed on a bionic robot designed to test whether teaching in a foreign language affected students' interest in STEM subjects. The study showed that students are more likely to be motivated to learn STEM when taught in easy-to-understand languages. Elizabeth Casey et al. [107] tested the STEM teaching results of Floor-Robots for Spanish primary school students who speak English as their mother tongue. Chicas et al. [108] aimed to design a low-cost educational robot to attract more students to participate in robotics competitions to test their STEM abilities. Yuen et al. [109] developed a modular combat

robot as a programming learning tool for STEM education. The combat robot was connected to a mobile application controller through Bluetooth technology. The mobile application controller could control the movement of the combat robot through the joystick interface. Students could develop different combat modules, design different gameplay for the combat robot, and conduct gamification STEM learning. Fachantidis et al. [110] built an Android-based social robot designed to act as a student's companion to inspire their achievement in STEM. Velentza et al. [150] designed a social robot, STIMEY, according to the needs of various stakeholders (teachers, students, and parents) in different European countries for STEM education robots, to serve as a companion for primary and secondary school students in STEM learning. It showed that STIMEY received positive feedback from students and improved their STEM abilities. Yang et al. [111] proposed a virtual educational robot-based learning system, called "AR Bot", designed to support computational thinking and STEM education learning activities. Rahman et al. [112] aimed to develop a set of evaluation indicators and methods to evaluate students' learning effect and the interaction effect between learners and robots in STEM education supported by robots. Evaluation indexes included evaluation of student outcomes (safety, usability, etc.), participation, cognitive load, group collaboration, etc.

STEAM education extends Art education to STEM education. STEAM educational robots are also popular in research. For example, Jeon et al. [113] developed an after-school drama project for primary school students using interactive robots of different types and functions. Students used robots as partners and actors to rehearse plays. The result showed that this learning style greatly stimulated students' enthusiasm for learning and promoted students' STEAM-related skills to a certain extent. Barnes et al. [114] were also combining educational robotics with theater knowledge for after-school programs. By the project, students could learn new skills about technology and engineering (programming, robot control, and other scientific and engineering concepts), art and design (writing the script, stage, and props design, preparation of music and sound effects, collaboration, discussions, negotiations, role assignment, and assessment) and coexist with a robot (facing the philosophy and ethical issues). Based on the Robobo robot, Naya et al. [37] discussed the functions that a new generation of educational robots should have, and developed a STEAM course for high school students, using PBL (Project-based learning) learning method. It aimed to give students a deeper understanding of the new generation of educational robots.

University education. Rácz et al. [115] introduced the development process of PlatypOUs, an innovative mobile robot platform and demonstration tool designed at the Bejczy Antal Center of Intelligent Robotics of Óbuda University and the related Robotic Special College for educational purposes. Bora-Laya et al. [116] proposed the BEAM (Biology, Electronics, Aesthetics, and Mechanics) robot technology to enhance STEM knowledge and skills among engineering students in the electrical, electronic, and mechanical fields through its design, construction, and operational development. Porras et al. [117] developed a robot competition project based on

STEM education in an AI course in a technical university program.

In the development of relevant courses or projects, many colleges and universities set up specialized STEM robot courses. Robotics Academy of Carnegie Mellon University is committed to studying how teachers use robots in classroom teaching, how to use the media of robotics technology to enhance learners' interest in interdisciplinary technology, and how to promote the integrated application of robots and education. Dean of the School of Robotics pointed out that no matter how technology develops, computer programming, electronically embedded systems, engineering design, and mathematics are all eternal issues, and the knowledge and skills in these fields are all included in the new comprehensive discipline of robotics [118]. Philips Marburg University designs Robotikum [119], a workshop designed as an adaptive learning scenario, to use humanoid robots to foster computational thinking in students without programming knowledge (middle and high school level).

(3) **After-class education.** ITRs mostly exist as learning tutors to take advantage of the ITR's synthesis and complexity, cultivating students' comprehensive capacity to practice innovation ability, and encouraging students to solve problems with science, technology, engineering, and mathematics knowledge [151]. Konijn et al. [120] recorded the results of students learning from the ITR in languages and STEM tasks. The results showed that pupils' ability and performance were significantly improved by learning from ITRs.

Also, the ITRs can help students consolidate their knowledge after class, for example, provide appropriate examinations after class according to the student's learning results in classes. Moreover, when students encounter fusions, robots provide answers based on existing knowledge and experience. Yueh et al. [121] leveraged an educational robot called Julia to read with children in the library. Julia provided conversation and discreet support during the children's reading time, which made children desirable to read.

(4) **Special education.** The ITRs can also be leveraged in special education. Meghdari et al. [137] introduced an intelligent robotic platform built for children with hearing disabilities. The robotic platform addressed the challenges by teaching Persian Sign Language to children. Giannopulu et al. [138] overcame the shortcomings of the experiments conducted on Japanese and French children with ASD by recording the heart rate activation and the emotional feelings of children using ITRs, to help order interpersonal synchronization in ASD children. Al-Tae et al. [139] investigated the acceptance of a humanoid ITR as an assistant applied in children's diabetes management.

(5) **Practical skills.** Except for the general courses in class, ITRs can also impart practical skills including social skills, hands-on skills, physical knowledge, language ability, and cognition ability.

Social skills. Research by Mohanan et al. [123] emphasized the role of intelligent tutoring systems in promoting social-emotional learning. These ITS incorporate virtual agents that provide personalized feedback, guidance, and emotional support to students. By interacting with these agents, students

can develop empathy, self-awareness, and social awareness. Furthermore, research by Levinson et al. [122] demonstrated that ITRs integrated with educational systems can positively influence students' social engagement and facilitate students developing social skills in summer camp.

Hands-on skills. At the K-12 and higher levels, robotics education has rapidly developed in significance, and robotics serve as teachers to help students realize the purpose of quickly acquiring the basics of mechanisms, assembling, and constructing. Takacs et al. [124] mainly focused on educational kits on the market and analyzed different attributes of the robotics kits. Among all robotics kits, LEGO Mindstorms [125] incorporating adaptive learning features, assessing students' performance, and adapting the content accordingly, seemed like handcraft teachers who provide an interactive learning experience where students can program and control their movements, promoting engagement and hands-on learning. Gerber et al. [126] designed robots based on LEGO Mindstorms to support experiments for education and even research, which are low-cost and can assist elementary, middle, and high school students in finishing rich activities. In tertiary education, Yi et al. [127] guided undergraduate students in designing educational robotics on a platform called DARwIn-HP. Students constructed their educational robots according to their thoughts and ideas, which could not only help all students learn the fundamental theory but also participate in the practice and evaluation. Nusayr et al. [128] showed a case study on educational robotic programming camps that helped teens to shape teens' knowledge in the computer science field and inspired their interests in programming. Huang et al. [129] adopted an intelligent robot to imitate the behaviors of patients, training nursing students, and teaching them to offer appropriate treatments according to corresponding symptoms. However, the ITR cannot record and track the improvements of both the students and patients.

Physical skills. Yang et al. [130] improved current physical education with AI technology. The authors designed a hybrid physical education robot to achieve personalized education for students.

Language ability. The ITR has also been implemented as a tutor in first- and second-language teaching [21], [131], [132]. For instance, Lee et al. [133] summarized the application of intelligent educational robots teaching English. When students learn languages, effective interaction benefits their improvement. ITRs provide students with a real-life humanoid appearance. Therefore, students feel more natural when stay and learn with ITRs. Schmidt et al. [134] indicated that various whole-body movements would help students improve the efficiency of learning vocabulary. And the body gestures and movements of ITRs are abundant.

Cognition ability. ITRs can perceive student affection and then provide personalized learning strategies. Knowing the affection of students is an important goal as it reflects students' needs and attitudes toward the study. Helping students adjust emotions and affections to positivity can enhance their good behaviors and help to develop marvelous interests in intelligent applications. Ziouziou et al. [135] created an intelligent robot to deliver the stories that climate change might lead to

brehtaking damage to Earth. Müller et al. [136] explored the intriguing possibilities of combining natural language processing with cognitive systems for automated suggestions and tutoring for students. Specifically, they investigated the potential of using cognitive software (i.e., IBM Watson) as a tool to develop a virtual tutor capable of answering common questions from students. While the results highlight the future potential of such systems in education, they currently suggest that this technology can only substitute tutors in very limited and specific scenarios.

2) *Intelligent Tutoring Robots in Tutoring Support: (1) Learning companion.* The mode of peer-to-peer has fewer limitations than the teacher-to-student mode. Since it is easier for students to stay with peers than strict adults, such robots reduce the tension and oppression when students are getting along with them, and encourage interactive learning, making students more interested in activities related to study [99]. Students need a platform, like an ITR companion, to express their experiences and thoughts, which makes their life richer and more beautiful. And parents and teachers can hear students' voices during education instead of after graduation. Shiomi et al. [140] utilized two educational robots as companions to concentrate on praising children during their learning time, and the result showed that the robots are effective in enhancing children's learning. Verner et al. [141] conducted a series of experiments focusing on the impact of using ITRs as companions in class.

(2) *Learn-through-play ITR.* ITRs combined with the concept of learn-through-play can enhance students' passion for studying. Positive gamified principles such as its flexible programming framework and a positive feedback mechanism. Nascimento et al. [142] proposed sBotics for both teachers and students. The rapid and positive feedback mechanism that can stimulate student interest in the games can be transferred into the learning process. Leonard et al. [143] used an ITR to help develop students' computational thinking by assigning tasks that create games using the software. The experimental results showed that students studied effectively in the environment combined with games. Schez-Sobrino et al. [144] modeled the RoboTIC, an intelligent gamified robot, to help students obtain tough and frustrating programming skills.

IV. DISCUSSION

With the development and popularity of AI technologies, the integration of AI and education will be more in-depth. Currently, many researchers are aiming to enhance teaching and learning efficiency. They are committed to exploring the application of robots in the field of education and have made significant progress. However, there are still some controversies and challenges worth pondering. In this section, we present the results of the systematic review literature, point out the controversies and challenges, and suggest the future research perspectives of ITRs.

A. RQ1: How does the construction of ITRs affect education?

With RQ1, we sought to clarify the general construction of ITRs in education and whether the construction of ITRs has

an impact on their acceptance by users. In this section, we also discuss simulated robots vs. real robots from the perspective of a hit concern of construction.

The construction of Intelligent Tutoring Robots (ITRs) is a multifaceted process that blends hardware design, sensor deployment, and advanced software development [42], [47]. Initially, the hardware design is foundational, enabling ITRs to mimic human-like movement capabilities with "joints" [43]. Concurrently, these robots are equipped to deliver instructional content through diverse mediums, such as electronic screens [7], enhancing their ability to engage with learners. Equally important are the sensors, which are crucial for ITRs to effectively perceive their surroundings [32]. These sensors facilitate a more interactive and responsive learning environment, allowing the robots to adapt to different educational settings. Complementing the hardware and sensor capabilities, the role of AI algorithms in the construction of ITRs is indispensable, primarily within the software development aspect. These algorithms are diverse, ranging from those enabling automated responses and learning analysis to sensor-based interaction, computer vision, and AI-driven emotional and facial recognition. For instance, the construction of Andruino-R2 [32] provides learning opportunities in intelligent automatic control and computer vision, thus enriching the educational field. The AI element here is evident in the robot's ability to interact with its environment using sensors and to perform tasks in computer vision, a key area of AI. Similarly, ITRs based on Robotic Process Automation (RPA) [44] offer automated intelligent responses to online students. These ITRs are embedded with advanced AI algorithms, including natural language processing, machine learning, knowledge representation, reasoning, massively parallel computing, and rapid domain adaptation. By observing students' learning behaviors, these ITRs iteratively analyze user processes. Studies have shown that students achieve higher average grades with the support of these RPA-based ITRs, demonstrating the effectiveness of integrating complex AI technologies into educational robots.

There is an interesting detail about the construction of the ITRs, while the construction cost of ITRs is typically expensive, some academics strive to reduce the cost [45], [46], [33]. However, Levinson et al. pointed out that both low-cost and high-cost educational robots can effectively engage young children in educational summer camp activities [122], suggesting that in some specific cases, low-cost robotic constructions may have the same impact on learning as high-cost ones.

Additionally, the appearance of robots is a significant area of research. Despite the presence of literature demonstrating the need for improvement and development of ITRs towards a humanoid appearance [48], [49], researchers argue that the impact of humanoid appearance on user acceptance is not definitive [50]. While some believe that humanoid appearance can facilitate the widespread adoption of robots in education [52], individual differences and cultural factors may also influence user acceptance [152]. Additionally, using more realistic platforms such as mobile robots for tasks involving movement or robotic arms for manipulation can provide students with better training opportunities [38], [7].

Therefore, there seems to be no definitive answer to what

structure and appearance should be adopted for ITRs. The design should depend on the target audience, needs, and application scenarios of the ITRs. For instance, a robot used for specific operational skill learning does not need to be designed in a human form, while one aimed at children as learning companions should give extra consideration to its appearance for better acceptance by children [153].

Considering the significant research attention received during the pandemic, we will briefly discuss the topic of “simulated robots vs. real robots” in the context of ITR construction, aiming to provide valuable insights. Robots are generally classified into real robots and simulated robots based on their physical existence. Real robots are tangible machines with physical forms and mechanical structures [34], [35], and they are the initially well-known type of robots. On the other hand, simulated robots do not have a physical presence but are simulated through programs and algorithms [36]. They are commonly used in virtual assistants and chatbots. Both types of robots are applied in the field of education. Although numerous previous studies have indicated that real robots exhibit better interaction effects compared to simulated robots, and can effectively enhance learning motivation and efficacy [154], [155]. However, with the growing popularity of ubiquitous learning facilitated by the Internet, simulated educational robots offer higher cost-effectiveness. Therefore, the design of ITRs’ construction should consider specific learning environments, needs, educational objectives, and other external factors in the overall educational landscape. For instance, when applying ITRs in large-scale online learning platforms, embedding a virtual representation directly within the software system would be more appropriate.

B. RQ2: What AI technologies enable ITRs to be “intelligent”?

With RQ2, we tried to summarize which AI technologies are leveraged in ITRs and have a positive impact on education. Prior studies on AI for education have shown enough shreds of evidence and stressed the benefits of AI technologies that are effective in improving the learning process [156], [157], [158]. Typically, as shown in this study, the AI technologies such as knowledge tracing, affective computing, and intelligent Q&A seem to be necessary for the field of ITRs, leading to innovative solutions and products. Ideally, ITRs possess the capability to customize learning content and teaching methods based on students’ individualized needs and learning styles [61]. However, the current implementation of ITRs faces several limitations.

To be concrete, many scholars provide the latest research advances and methods on the application of knowledge tracing in ITRs [60], [61], [64], [67]. They applied knowledge tracing in massive open online courses and intelligent tutoring systems [62], including the use of methods such as recurrent neural networks [59] and dynamic Bayesian networks [57], [58]. Those studies offer valuable insights and practical experience in knowledge tracing techniques for ITRs. However, research on the combination of potential knowledge tracing and ITRs are relatively rare, resulting in an underexplored landscape

where knowledge tracing and ITRs intersect. Consequently, further research efforts are needed to bridge this gap. Additionally, the absence of a standardized baseline to evaluate knowledge tracing metrics in robots remains a challenge. Moreover, the knowledge tracing algorithms are effective in ideal situations but do not have the capabilities to interact with the real world [63], [65], [66]. This is likely due to the inherent complexities of the two fields. Knowledge Tracing in educational environments involves monitoring and analyzing students’ learning progress, while ITR aims to interact with students and facilitate learning. As both fields are currently in the exploration and development stage, integrating these two aspects requires more complex algorithms and poses certain difficulties.

Besides, numerous studies collectively contribute to the understanding of the human emotion in human-robot interactions [68], [69], [70], [71], and we can infer from the research results that the ITRs with effective affective computing algorithms provide better services for the education field and be more suitable for the personalized development of students [73], [74], [77]. However, it is worth noting that many of these studies were conducted in informal learning environments and lacked experimental or quasi-experimental designs [159], [75], [76], leading to ongoing debates about the actual effectiveness of ITRs. Robots with emotional processing capabilities can generate appropriate emotional responses and adapt to their environment, taking ethical considerations into account [160], [78]. The social and emotional interaction between robots and learners can enhance the acceptance of robots in educational settings [161]. Thus, the ITRs with emotion-sensing capabilities can enhance learners’ motivation and increase their interest in learning by recognizing learners’ emotional states and responding accordingly [79], [80], [81], [82]. However, the development of affective computing technology still requires further progress to achieve the desired level of emotional perception and interaction in ITRs. Firstly, emotions can be expressed and perceived in diverse ways, including language, facial expressions, vocal tones, and body language. This implies that ITRs should be able to recognize emotions based on multiple sensor devices and integrate multi-modal data for emotion recognition. Secondly, in real-world environments, emotion recognition and expression are more complex compared to controlled experimental settings [92], posing challenges for practical application. Thirdly, it is crucial to gather more quantitative labels or ratings to accurately assess the ITR’s sentimental understanding, especially those robots designed for kids. Special attention should be given to capturing distinctive behaviors exhibited by children that may be difficult for adults to understand. Additionally, ITRs should be capable of switching between several modes based on a child’s performance. Moreover, it is important to consider the limitations of relying excessively on robot-provided solutions, as customization of morphology according to specific contexts may be lost in some cases. Therefore, careful consideration of the application scope and environment of robots is necessary.

Current research discusses the growing focus on the interaction between ITRs and human beings [86], [87], [88], [89], [83]. It also emphasizes the importance of language

interaction between teachers/ students and the role of ITRs in understanding students' knowledge and thinking processes [87]. It suggests that establishing a good interaction process between teachers and students can enhance students' learning outcomes [90], [91]. However, there are some limitations and areas for future research. Firstly, although some studies mention the embedding of AI algorithms to understand students' grasp of knowledge [84], it lacks specific details on how this is employed. Secondly, while some research highlights the significance of effective interaction processes between ITRs and students, it does not delve into the specific strategies or methods to establish such processes. To address the first issue, it is crucial to emphasize the development of transparent and interpretable AI systems. Research in Explainable Artificial Intelligence (XAI) focuses on making the AI decision-making process transparent and interpretable, aiding in understanding how to use AI algorithms to assess students' knowledge [162]. Additionally, consideration can be given to integrating cultural and psychological factors into the learning and cognitive algorithms of AI systems. This approach aligns with the development of AI systems capable of understanding, producing, and communicating "meaning" in a manner that is congruent with human cultural and psychological systems [163]. Regarding the second issue, attempting to develop human-like intelligence in ITRs can establish social intelligence and empathetic behavior [164]. However, this involves using various AI techniques to model such behaviors, the impact of these social behaviors on user interaction and learning, and how to measure and evaluate these impacts [165]. Additionally, there is a lack of comprehensive analysis of the practical applications of ITRs and their impact on education. Lastly, although some studies mention the importance of intelligent question-answering systems as a reflection of the intelligence of ITRs [95], [84], it does not discuss the current limitations or challenges in developing such systems. Therefore, there is much room for improvement. For example, focus on developing advanced AI algorithms for understanding students' knowledge, applying and evaluating the findings from existing studies, and enhancing intelligent question-answering systems to improve the overall intelligence and effectiveness of ITRs. Moreover, explore methods for improving the question and answering capabilities of ITRs, including natural language understanding, knowledge representation, and reasoning techniques. Most importantly, investigate the practical implementation of these findings and explore how they can be integrated into educational robot systems to enhance their functionality and performance.

C. RQ3: How are ITRs applied in educational contexts?

With RQ3, we want to investigate another highly-anticipated topic how the ITRs show their advantages in realistic educational situations. Overall, ITRs help education in two broad directions: subject education and tutoring support. On the one hand, in the subject education, ITRs provide guidance and support in teaching a variety of subjects. For example, in STEM education, ITRs help students answer general questions, provide examples, and practice problems [12], [7]. In

STEM subjects such as science and math, intelligent tutoring robots provide relevant knowledge, experimental demonstrations, and interactive learning experiences [96], [104], [115]. In language teaching, ITRs provide grammar explanations, vocabulary learning, and oral training [21], [133], [134]. ITRs also contribute to the enhancement of learners' empathy, social and emotional skills, spatial awareness, and problem-solving abilities [135], [166], [16], [167]. On the other hand, ITRs can also be used to support teachers in the teaching process, similar to teaching aids. ITRs provide teachers with teaching resources [142], lesson plan design and learning assessment tools to support teaching and improve teachers' effectiveness and students' learning outcomes [142], [143], [144].

Regarding subject education, in the current teaching system, a qualified ITR is supposed to have the attribute of creativity and flexibility in teaching, proficiency in the school curriculum, and perception of human affection. Although the teaching plans vary from school to school, the plans need to satisfy the development of 21st-century learning skills [168], which include abilities such as adaptability and creativity, initiative and critical thinking [126], [125], [124], teamwork and social skills [123], [122], problem-solving and productivity, leadership, and scientific reasoning. Despite ITRs having the potential to assist students in acquiring practical skills [126], [128], [130], several drawbacks should be considered. Firstly, the accuracy of recognition in ITR systems is not sufficiently high. Several factors contribute to this challenge faced by ITRs, including limited scenario-specific training data, a scarcity of educational data, and student privacy concerns limiting data diversity [137], [130]. Besides, current AI algorithms often fail to grasp the context of interactions [122], [123], complicating the accurate recognition and interpretation of educational content by ITRs. A significant issue is the integration of information from multiple sources (audio, visual, etc.), where difficulties in merging these modalities can decrease recognition accuracy [169]. Enhancing data quality and diversity, improving ITR-student interactions [170], or incorporating advanced AI algorithms can notably increase ITR accuracy in educational settings. These strategies enhance contextual understanding, encourage user feedback integration, and facilitate multimodal interaction analysis [171], making ITRs more aligned with actual educational requirements. Secondly, the existing research often suffers from small sample sizes, making it challenging to establish a strong case for using ITRs to improve students' interest in physical movements. Thirdly, there is a lack of comprehensive research on the application of ITRs in language teaching. Additionally, measuring children's cognitive levels, such as empathy, poses difficulties. For instance, the measurement of learners' abilities and cognition in a natural learning environment requires collaboration between professional research teams and experienced teachers, since students may engage in behavior beyond expectations. However, due to individual differences, different teams and experts may obtain varying measurement results, limiting the provision of objective support for subsequent analysis.

According to 52 out of 105 primary studies, the use of ITRs to enhance STEM education is a significant research area. Regarding educational technology, three theories on integrating

ITRs and STEM subjects have emerged: the natural integration view, the knowledge construction view, and the situation construction view [172]. The natural integration view treats ITRs as a knowledge object [173], while the knowledge construction view considers ITRs as technical tools that support the construction of integrated knowledge [174]. The situation construction view sees ITRs as tools for situation construction and integration [175]. Therefore, the usage of ITRs in STEM education can be divided into two parts. On the one hand, ITRs are the subject achievements of students' research. Students need to integrate interdisciplinary knowledge to design the appearance and function of robots so that they can solve practical problems in daily life. It stimulates students' learning motivation and interest through personal creation. On the other hand, ITRs are also seen as effective tools to help develop students' team skills. Although abundant literature has proved through empirical studies that the application of ITRs in STEM education can promote the development of preschool children's computational thinking and other abilities, they did not carry out the rigorous quasi-experimental design. The researchers only evaluated the students' pre-and-post-test learning effect, and the advantages of using ITRs in STEM education compared to other teaching methods were not proved. At the same time, the number of research objects was too small so the results obtained were not widely representative, which should be further studied with more participants and more diverse environments. A investigation of the 52 literature on STEM education from another perspective shows that through features such as personalized learning support, interactive teaching, and real-time feedback, ITRs play different roles and enablers across all age groups, providing targeted educational and learning experiences that facilitate their development and growth in all areas [96], [97], [98], [149]. In early childhood education, ITRs communicate and learn from young children in an interactive and entertaining way, helping them to develop language skills, cognitive skills, and creativity [99], [100]. They provide personalized learning content and activities tailored to young children to promote their holistic development [150], [102], [103]. In primary and secondary education, ITRs act as learning companions and support teachers for primary school and high-school students, helping them to master basic subject knowledge and increase their interest and motivation in learning [104], [105], [106], [107], [108], [109]. Through adaptive learning systems and AI algorithms, ITRs tailor learning plans to provide personalized content and challenges for students [113], [114], [37]. ITRs can also help students develop problem-solving skills, critical thinking, and innovation [110], [150], [111], [112]. In university education, or adult and vocational training, ITRs provide flexible learning opportunities and personalized educational support [115], [116], [117], [118], [119].

To encapsulate, ITRs play different roles in education, many functions of robots are mutually supportive, interconnected, and integrated. We are not supposed to completely separate the functions of robots, but regard them as a whole. This field necessitates a collaborative effort from researchers worldwide. The progress in machine learning and artificial intelligence algorithms is crucial to improving the recognition and response

capabilities of ITRs. Moreover, conducting diverse and extensive experimental studies is vital. These studies should aim not only to enhance the scope and variety of research but also to ensure the generalizability and representativeness of the outcomes. Such comprehensive research efforts are essential to advancing the effectiveness and application of ITRs in educational settings.

D. Future Perspective

1) *Promote intelligence and personalized interaction:* With the development of various AI technologies and the deepening of study related to ITRs, the future ITRs will be more intelligent. Because it is related to whether the learner can continue to maintain interest in it. From the perspective of appearance alone, a good-looking anthropomorphic robot is more acceptable to the learner [48]. Learners of different age groups pay different attention to ITRs. The younger age group pays more attention to the appearance of ITRs, while the learners of high school or undergraduate pay more attention to the experience and function [176]. Moreover, the appearance design suitable for different teaching contents is also different [177]. Therefore, the appearance design of ITRs should tend to be diversified, and different appearance designs are adopted according to the different users and roles it plays.

But meanwhile, the robot's function and user's experience are also important. Benefits from the development of AI technologies such as affective computing, knowledge tracing, and so on. ITRs' function has an extremely broad space for development. However, there is still a lack of research on the application of these technologies in practical teaching and learning scenarios. In general, the intelligent robot could provide more accurate and effective feedback and intervention, providing a more intelligent and personalized interactive experience and learning service.

2) *Future effective applications of intelligent tutoring robots:* With the continuous advancement of technology, ITRs hold vast potential in the field of education. Firstly, personalized learning guidance stands out as one of the significant applications of ITRs. Leveraging intelligent algorithms and big data analysis, robots can gain a profound understanding of students' learning needs, styles, and proficiency levels, thereby offering customized educational programs. However, there are still existing technological limitations. For instance, robots currently struggle with comprehending and addressing students' emotional states, lacking sensitivity towards their emotional needs. Overcoming this challenge necessitates further advancements in emotion recognition technology, enabling robots to accurately identify and understand students' emotions. Secondly, language learning represents another important application scenario. ITRs can leverage speech recognition and synthesis technologies to engage students in voice interactions and oral training. Existing research indicates that students find the support of ITRs particularly enjoyable in language learning, resulting in faster learning, increased knowledge acquisition compared to traditional classrooms, and better long-term outcomes [178]. Additionally, ITRs can create gamified environments for language learning, stimulating students'

interest and motivation. Lastly, ITRs can integrate powerful AI language models like ChatGPT. Leveraging their robust natural language processing and generation capabilities, these robots can function as teaching assistants or learning companions, delivering instant answers, clarification, and guidance to students through interactive conversations.

V. CONCLUSION

In this review, we have investigated ITRs from three perspectives. The first aspect is the scientific construction of ITRs, the second aspect is the core component of making ITRs intelligent, which involves the adoption of AI algorithms, and the third aspect is the current applications of ITRs in education.

AI technology provides the “brain” for ITRs, enabling them to effectively facilitate the learning process for students. In this paper, we attempted to summarize the positive impacts of AI technologies carried by ITRs on education. We conducted an in-depth analysis of common AI technologies found in ITRs, such as knowledge tracing, affective computing, and intelligent Q & A. Ideally, ITRs should possess the ability to customize learning content and teaching methods according to students’ individualized needs and learning styles. However, there are still challenges in the current AI technologies used in ITRs. Firstly, there is a lack of diversity in the types of AI applications within ITRs, with intersecting fields yet to be fully explored. Diverse AI applications in ITRs can integrate multi-modal communication like visual, auditory, and kinesthetic to support different learning styles. For example, utilizing AI for gesture and facial expression analysis, combined with adaptive learning algorithms, enables customized teaching strategies. This personalized approach meets various learning abilities, underscoring the importance of AI diversity in developing effective and inclusive ITRs. Secondly, there is a lack of standardized benchmarks for assessing the effectiveness of AI technologies in ITRs. Additionally, while some studies emphasize the importance of effective interaction processes between ITRs and students, specific strategies or methods for establishing such processes have not been thoroughly explored. Therefore, further research has great potential for improvement, and researchers from various disciplines need to work together to fill these gaps.

In real educational scenarios, ITRs mainly have two applications: as teachers of subject education and as intelligent tutoring support. In subject education, ITRs provide guidance and support for teaching various subjects, flexibly and proficiently mastering school curricula as well as perceiving human emotions. We have focused on analyzing their roles in general courses, STEM courses, practical skills, and special education in this paper. However, the current accuracy of ITRs in recognizing these roles is still insufficient. Additionally, the sample size in research studies is often small, and the individual differences among students make it challenging to establish compelling cases for the improvement of subject education through ITRs. With technological advancements and in-depth research, ITRs are expected to play an even greater role in the future, creating better educational experiences for students and teachers.

REFERENCES

- [1] K. Ahmad, W. Iqbal, A. El-Hassan, J. Qadir, D. Benhaddou, M. Ayyash, and A. Al-Fuqaha, “Data-driven artificial intelligence in education: A comprehensive review,” *IEEE Transactions on Learning Technologies*, vol. 17, pp. 12–31, 2024.
- [2] J. Leoste and M. Heidmets, “The impact of educational robots as learning tools on mathematics learning outcomes in basic education,” in *Digital Turn in Schools—Research, Policy, Practice*, pp. 203–217, Springer, 2019.
- [3] I. Papadopoulos, R. Lazzarino, S. Miah, T. Weaver, B. Thomas, and C. Koulouglioti, “A systematic review of the literature regarding socially assistive robots in pre-tertiary education,” *Computers Education*, vol. 155, 2020.
- [4] S. Papert, “What is logo? who needs it,” *Logo philosophy and implementation*, pp. 4–16, 1999.
- [5] C. J. Solomon and S. Papert, “A case study of a young child doing turtle graphics in logo,” in *Proceedings of the June 7-10, 1976, national computer conference and exposition*, pp. 1049–1056, 1976.
- [6] S. Papert, “Children, computers and powerful ideas,” *Harvester Press (United Kingdom)*. DOI, vol. 10, pp. 978–3, 1980.
- [7] S. Guerreiro-Santalla, F. Bellas, and A. Mallo, “Introducing high school students in natural interaction through the robobo educational robot,” in *ROBOT2022: Fifth Iberian Robotics Conference: Advances in Robotics, Volume 1*, pp. 500–512, Springer, 2022.
- [8] T. Belpaeme, J. Kennedy, A. Ramachandran, B. Scassellati, and F. Tanaka, “Social robots for education: A review,” *Science robotics*, vol. 3, no. 21, p. eaat5954, 2018.
- [9] Y. Zhang, R. Luo, Y. Zhu, and Y. Yin, “Educational robots improve k-12 students’ computational thinking and stem attitudes: systematic review,” *Journal of Educational Computing Research*, vol. 59, no. 7, pp. 1450–1481, 2021.
- [10] Y. Zhang and Y. Zhu, “Effects of educational robotics on the creativity and problem-solving skills of k-12 students: a meta-analysis,” *Educational Studies*, pp. 1–19, 2022.
- [11] S. Tselegkaridis and T. Sapounidis, “Exploring the features of educational robotics and stem research in primary education: A systematic literature review,” *Education Sciences*, vol. 12, no. 5, p. 305, 2022.
- [12] L. F. Llamas, A. Paz-Lopez, A. Prieto, F. Orjales, and F. Bellas, “Artificial intelligence teaching through embedded systems: A smartphone-based robot approach,” in *Robot 2019: Fourth Iberian Robotics Conference: Advances in Robotics, Volume 1*, pp. 515–527, Springer, 2020.
- [13] M. Naya-Varela, S. Guerreiro-Santalla, T. Baamonde, and F. Bellas, “Robobo smartcity: An autonomous driving model for computational intelligence learning through educational robotics,” *IEEE Transactions on Learning Technologies*, 2023.
- [14] I. Storjak, A. S. Krzic, and T. Jagust, “Elementary school pupils’ mental models regarding robots and programming,” *IEEE Transactions on Education*, vol. 65, no. 3, pp. 297–308, 2022.
- [15] M. Pacheco, R. Fogh, H. H. Lund, and D. J. Christensen, “Fable ii: Design of a modular robot for creative learning,” in *2015 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 6134–6139, IEEE, 2015.
- [16] O. Mubin, C. J. Stevens, S. Shahid, A. Al Mahmud, and J.-J. Dong, “A review of the applicability of robots in education,” *Journal of Technology in Education and Learning*, vol. 1, no. 209-0015, p. 13, 2013.
- [17] L. Yuan, S. Zhang, M. Lei, Y. Qin, and W. Zhang, “High-quality developments in technology-enabled education: The frontiers of artificial intelligence, blockchain, and robots,” *Open Education Research*, vol. 27, pp. 4–16, 2021.
- [18] M. A. Goodrich, A. C. Schultz, et al., “Human–robot interaction: a survey,” *Foundations and Trends® in Human–Computer Interaction*, vol. 1, no. 3, pp. 203–275, 2008.
- [19] Y.-W. Cheng, P.-C. Sun, and N.-S. Chen, “The essential applications of educational robot: Requirement analysis from the perspectives of experts, researchers and instructors,” *Computers & education*, vol. 126, pp. 399–416, 2018.
- [20] Y. Zhang and Y. Wang, “Robot empowered innovation and change in future education: A review of international robotic teachers,” *Open Education Research*, vol. 25, no. 6, pp. 83–92, 2019.
- [21] R. van den Berghe, J. Verhagen, O. Oudgenoc-Paz, S. Van der Ven, and P. Leseman, “Social robots for language learning: A review,” *Review of Educational Research*, vol. 89, no. 2, pp. 259–295, 2019.
- [22] V. Lin, H.-C. Yeh, and N.-S. Chen, “A systematic review on oral interactions in robot-assisted language learning,” *Electronics*, vol. 11, no. 2, p. 290, 2022.

- [23] V. Rosanda and A. Istenic Starcic, "The robot in the classroom: a review of a robot role," in *International Symposium on Emerging Technologies for Education*, pp. 347–357, Springer, 2019.
- [24] I. U. Cayetano-Jiménez, E. A. Martínez-Ríos, R. Bustamante-Bello, R. A. Ramírez-Mendoza, and M. S. Ramírez-Montoya, "Experimenting with soft robotics in education: A systematic literature review from 2006 to 2022," *IEEE Transactions on Learning Technologies*, vol. 17, pp. 1261–1278, 2024.
- [25] E. Mangina, G. Psyrra, L. Screpanti, and D. Scaradozzi, "Robotics in the context of primary and preschool education: A scoping review," *IEEE Transactions on Learning Technologies*, vol. 17, pp. 342–363, 2024.
- [26] W. Johal, "Research trends in social robots for learning," *Current Robotics Reports*, vol. 1, no. 3, pp. 75–83, 2020.
- [27] H. Woo, G. K. LeTendre, T. Pham-Shouse, and Y. Xiong, "The use of social robots in classrooms: A review of field-based studies," *Educational Research Review*, vol. 33, p. 100388, 2021.
- [28] B. P. Woolf, *Building intelligent interactive tutors: Student-centered strategies for revolutionizing e-learning*. Morgan Kaufmann, 2010.
- [29] J. Yang and B. Zhang, "Artificial intelligence in intelligent tutoring robots: A systematic review and design guidelines," *Applied Sciences*, vol. 9, no. 10, p. 2078, 2019.
- [30] B. Kitchenham and S. Charters, "Guidelines for performing systematic literature reviews in software engineering," vol. 2, 01 2007.
- [31] L. Toh, A. Causo, P.-W. Tzuo, I.-M. Chen, and S. Yeo, "A review on the use of robots in education and young children," *Educational Technology Society*, vol. 19, p. 148–163, 01 2016.
- [32] F. M. Lopez-Rodriguez and F. Cuesta, "An android and arduino based low-cost educational robot with applied intelligent control and machine learning," *Applied Sciences*, vol. 11, no. 1, p. 48, 2020.
- [33] R. Balogh, L. Fundarek, and M. Lipkova, "Open design meets robotics-customizable educational robot construction system," in *International Conference on Robotics in Education (RIE)*, pp. 137–149, Springer, 2022.
- [34] R. A. Brooks and M. J. Mataric, "Real robots, real learning problems," *Robot learning*, pp. 193–213, 1993.
- [35] S. Carpin, M. Lewis, J. Wang, S. Balakirsky, and C. Scrapper, "Usar-sim: a robot simulator for research and education," in *Proceedings 2007 IEEE International Conference on Robotics and Automation*, pp. 1400–1405, IEEE, 2007.
- [36] F. Xiang, Y. Qin, K. Mo, Y. Xia, H. Zhu, F. Liu, M. Liu, H. Jiang, Y. Yuan, H. Wang, *et al.*, "Sapien: A simulated part-based interactive environment," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 11097–11107, 2020.
- [37] M. Naya, G. Varela, L. Llamas, M. Bautista, J. C. Becerra, F. Bellas, A. Prieto, A. Deibe, and R. J. Duro, "A versatile robotic platform for educational interaction," in *2017 9th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS)*, vol. 1, pp. 138–144, IEEE, 2017.
- [38] F. Bellas, A. Mallo, M. Naya, D. Souto, A. Deibe, A. Prieto, and R. J. Duro, "Steam approach to autonomous robotics curriculum for high school using the robobo robot," in *Robotics in Education: Current Research and Innovations 10*, pp. 77–89, Springer, 2020.
- [39] F. Bellas, M. Naya, G. Varela, L. Llamas, A. Prieto, J. C. Becerra, M. Bautista, A. Faina, and R. Duro, "The robobo project: Bringing educational robotics closer to real-world applications," in *Robotics in Education: Latest Results and Developments*, pp. 226–237, Springer, 2018.
- [40] S. Papert and I. Harel, "Situating constructionism," *constructionism*, vol. 36, no. 2, pp. 1–11, 1991.
- [41] J. Li, "The benefit of being physically present: A survey of experimental works comparing copresent robots, telepresent robots and virtual agents," *International Journal of Human-Computer Studies*, vol. 77, pp. 23–37, 2015.
- [42] A. M. Hashan, A. Haidari, S. Saha, T. Paul, *et al.*, "Computer numerically controlled drawing robot based on computer-aided design," *Journal of Mechanical, Civil and Industrial Engineering*, vol. 2, no. 1, pp. 06–10, 2021.
- [43] D. Sáenz Zamarrón, N. I. Arana de las Casas, E. García Grajeda, J. F. Alatorre Ávila, and J. U. Naciff Arroyo, "Educational robot arm development," *Computación y Sistemas*, vol. 24, no. 4, pp. 1387–1401, 2020.
- [44] Y.-H. Hu, J. S. Fu, and H.-C. Yeh, "Developing an early-warning system through robotic process automation: Are intelligent tutoring robots as effective as human teachers?," *Interactive Learning Environments*, pp. 1–14, 2023.
- [45] C. Vandevelde, F. Wyffels, M.-C. Ciocci, B. Vanderborght, and J. Saldien, "Design and evaluation of a diy construction system for educational robot kits," *International Journal of Technology and Design Education*, vol. 26, no. 4, pp. 521–540, 2016.
- [46] F. M. López-Rodríguez and F. Cuesta, "Andruino-a1: Low-cost educational mobile robot based on android and arduino," *Journal of Intelligent & Robotic Systems*, vol. 81, no. 1, pp. 63–76, 2016.
- [47] D. Hayosh, X. Liu, and K. Lee, "Woody: Low-cost, open-source humanoid torso robot," in *2020 17th International Conference on Ubiquitous Robots (UR)*, pp. 247–252, 2020.
- [48] N. Reich-Stiebert, F. Eyssel, and C. Hohnemann, "Exploring university students' preferences for educational robot design by means of a user-centered design approach," *International Journal of Social Robotics*, vol. 12, no. 1, pp. 227–237, 2020.
- [49] P. Christodoulou, A. A. M. Reid, D. Pneumatikos, C. R. del Rio, and N. Fachantidis, "Students participate and evaluate the design and development of a social robot," in *2020 29th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*, pp. 739–744, IEEE, 2020.
- [50] M. Li, F. Guo, Z. Ren, and V. G. Duffy, "A visual and neural evaluation of the affective impression on humanoid robot appearances in free viewing," *International Journal of Industrial Ergonomics*, vol. 88, p. 103159, 2022.
- [51] E. A. Björling, B. Louie, P. Wiesmann, and A. C. Kuo, "Engaging english language learners as cultural informants in the design of a social robot for education," *Multimodal Technologies and Interaction*, vol. 5, no. 7, p. 35, 2021.
- [52] K. Klüber and L. Onnasch, "Appearance is not everything-preferred feature combinations for care robots," *Computers in Human Behavior*, vol. 128, p. 107128, 2022.
- [53] A.-M. Velentza, S. Pliaza, and N. Fachantidis, "Future teachers choose ideal characteristics for robot peer-tutor in real class environment," in *International Conference on Technology and Innovation in Learning, Teaching and Education*, pp. 476–491, Springer, 2020.
- [54] H. Admoni and B. Scassellati, "Social eye gaze in human-robot interaction: a review," *Journal of Human-Robot Interaction*, vol. 6, no. 1, pp. 25–63, 2017.
- [55] R. Pelánek, "Bayesian knowledge tracing, logistic models, and beyond: an overview of learner modeling techniques," *User Modeling and User-Adapted Interaction*, vol. 27, no. 3, pp. 313–350, 2017.
- [56] Z. Jin, K. Ma, K. Liu, and K. Ji, "Exercises recommendation in adaptive learning system," in *Proceedings of the 2nd International Conference on Big Data Technologies*, pp. 97–100, 2019.
- [57] M. V. Yudelson, K. R. Koedinger, and G. J. Gordon, "Individualized bayesian knowledge tracing models," in *International conference on artificial intelligence in education*, pp. 171–180, Springer, 2013.
- [58] B. van De Sande, "Properties of the bayesian knowledge tracing model," *Journal of Educational Data Mining*, vol. 5, no. 2, pp. 1–10, 2013.
- [59] C. Piech, J. Bassen, J. Huang, S. Ganguli, M. Sahami, L. J. Guibas, and J. Sohl-Dickstein, "Deep knowledge tracing," *Advances in neural information processing systems*, vol. 28, 2015.
- [60] S. Shen, Q. Liu, E. Chen, Z. Huang, W. Huang, Y. Yin, Y. Su, and S. Wang, "Learning process-consistent knowledge tracing," in *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, pp. 1452–1460, 2021.
- [61] Y. B. David, A. Segal, and Y. Gal, "Sequencing educational content in classrooms using bayesian knowledge tracing," in *Proceedings of the sixth international conference on Learning Analytics & Knowledge*, pp. 354–363, 2016.
- [62] S. Minn, Y. Yu, M. C. Desmarais, F. Zhu, and J.-J. Vie, "Deep knowledge tracing and dynamic student classification for knowledge tracing," in *2018 IEEE International Conference on Data Mining (ICDM)*, pp. 1182–1187, 2018.
- [63] S. Shen, Q. Liu, E. Chen, H. Wu, Z. Huang, W. Zhao, Y. Su, H. Ma, and S. Wang, "Convolutional knowledge tracing: Modeling individualization in student learning process," in *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR '20*, (New York, NY, USA), p. 1857–1860, Association for Computing Machinery, 2020.
- [64] T. Schodde, K. Bergmann, and S. Kopp, "Adaptive robot language tutoring based on bayesian knowledge tracing and predictive decision-making," in *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction*, pp. 128–136, 2017.
- [65] Y. Sun, L. Wang, Q. Xie, Y. Dong, and X. Lin, "Online programming education modeling and knowledge tracing," in *International Confer-*

- ence on Knowledge Science, Engineering and Management, pp. 259–270, Springer, 2020.
- [66] Q. Liu, Z. Huang, Y. Yin, E. Chen, H. Xiong, Y. Su, and G. Hu, “Ekt: Exercise-aware knowledge tracing for student performance prediction,” *IEEE Transactions on Knowledge and Data Engineering*, vol. 33, no. 1, pp. 100–115, 2021.
- [67] A. Ramachandran, S. S. Sebo, and B. Scassellati, “Personalized robot tutoring using the assistive tutor pomdp (at-pomdp),” in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 33, pp. 8050–8057, 2019.
- [68] J. Rhim, A. Cheung, D. Pham, S. Bae, Z. Zhang, T. Townsend, and A. Lim, “Investigating positive psychology principles in affective robotics,” in *2019 8th International Conference on Affective Computing and Intelligent Interaction (ACII)*, pp. 1–7, IEEE, 2019.
- [69] M. Chita-Tegmark, M. Lohani, and M. Scheutz, “Gender effects in perceptions of robots and humans with varying emotional intelligence,” in *2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, pp. 230–238, IEEE, 2019.
- [70] B. Fang, X. Guo, Z. Wang, Y. Li, M. Elhoseny, and X. Yuan, “Collaborative task assignment of interconnected, affective robots towards autonomous healthcare assistant,” *Future Generation Computer Systems*, vol. 92, pp. 241–251, 2019.
- [71] J. Yang, R. Wang, X. Guan, M. M. Hassan, A. Almogren, and A. Alsanad, “Ai-enabled emotion-aware robot: The fusion of smart clothing, edge clouds and robotics,” *Future Generation Computer Systems*, vol. 102, pp. 701–709, 2020.
- [72] R. Kaushik and R. Simmons, “Affective robot behavior improves learning in a sorting game,” in *2022 31st IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*, pp. 436–441, 2022.
- [73] C. Filippini, E. Spadolini, D. Cardone, and A. Merla, “Thermal imaging based affective computing for educational robot,” *Proceedings*, vol. 27, no. 1, 2019.
- [74] S. Spaulding, G. Gordon, and C. Breazeal, “Affect-aware student models for robot tutors,” in *AAMAS ’16: Proceedings of the 2016 International Conference on Autonomous Agents Multiagent Systems*, ACM, 2016.
- [75] E. Yadollahi, W. Johal, J. Dias, P. Dillenbourg, and A. Paiva, “Studying the effect of robot frustration on children’s change of perspective,” in *2019 8th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW)*, pp. 381–387, IEEE, 2019.
- [76] L.-E. Imbernón Cuadrado, Á. Manjarrés Riesco, and F. de la Paz López, “Fer in primary school children for affective robot tutors,” in *International Work-Conference on the Interplay Between Natural and Artificial Computation*, pp. 461–471, Springer, 2019.
- [77] M. Kraus, D. Betancourt, and W. Minker, “Does it affect you? social and learning implications of using cognitive-affective state recognition for proactive human-robot tutoring,” in *2023 32nd IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*, pp. 928–935, IEEE, 2023.
- [78] S. L. K. Gudi, S. Ojha, Sidra, B. Johnston, and M.-A. Williams, “A proactive robot tutor based on emotional intelligence,” in *Robot Intelligence Technology and Applications 5: Results from the 5th International Conference on Robot Intelligence Technology and Applications 5*, pp. 113–120, Springer, 2019.
- [79] L.-E. Imbernón Cuadrado, A. Manjarrés Riesco, and F. De La Paz Lopez, “Artie: An integrated environment for the development of affective robot tutors,” *Frontiers in computational neuroscience*, vol. 10, p. 77, 2016.
- [80] F. M. Ippoliti, J. V. Chari, and N. K. Garg, “Advancing global chemical education through interactive teaching tools,” *Chemical Science*, 2022.
- [81] M. Hirokawa, A. Funahashi, Y. Itoh, and K. Suzuki, “Adaptive behavior acquisition of a robot based on affective feedback and improvised teleoperation,” *IEEE Transactions on Cognitive and Developmental Systems*, vol. 11, no. 3, pp. 405–413, 2019.
- [82] J. G. Muñoz, B. C. Calderón, R. M. Melgar, and J. M. R. Alonso, “Importance of the use of interactive methodologies in primary education: gamification. didactic proposal,” *South Florida Journal of Development*, vol. 2, no. 1, pp. 264–274, 2021.
- [83] S. Guo, J. Lenchner, J. Connell, M. Dholakia, and H. Muta, “Conversational bootstrapping and other tricks of a concierge robot,” in *Proceedings of the 2017 ACM/IEEE international conference on human-robot interaction*, pp. 73–81, 2017.
- [84] S. Ji and T. Yuan, “Conversational intelligent tutoring systems for online learning: What do students and tutors say?,” in *2022 IEEE Global Engineering Education Conference (EDUCON)*, pp. 292–298, IEEE, 2022.
- [85] K. V. Hindriks and S. Liebens, “A robot math tutor that gives feedback,” in *International Conference on Social Robotics*, pp. 601–610, Springer, 2019.
- [86] L. F. de Medeiros, A. K. Junior, and A. Moser, “A cognitive assistant that uses small talk in tutoring conversation,” *International Journal of Emerging Technologies in Learning (Online)*, vol. 14, no. 11, p. 138, 2019.
- [87] B. He, M. Xia, X. Yu, P. Jian, H. Meng, and Z. Chen, “An educational robot system of visual question answering for preschoolers,” in *2017 2nd international conference on robotics and automation engineering (ICRAE)*, pp. 441–445, IEEE, 2017.
- [88] H. D. Nguyen, V. T. Pham, D. A. Tran, and T. T. Le, “Intelligent tutoring chatbot for solving mathematical problems in high-school,” in *2019 11th International Conference on Knowledge and Systems Engineering (KSE)*, pp. 1–6, IEEE, 2019.
- [89] A. A. Gunawan, P. R. Mulyono, and W. Budiharto, “Indonesian question answering system for solving arithmetic word problems on intelligent humanoid robot,” *Procedia Computer Science*, vol. 135, pp. 719–726, 2018.
- [90] W. Budiharto, A. D. Cahyani, P. C. Rumondor, and D. Suhartono, “Edurobot: intelligent humanoid robot with natural interaction for education and entertainment,” *Procedia computer science*, vol. 116, pp. 564–570, 2017.
- [91] S. Huang, “Design and development of educational robot teaching resources using artificial intelligence technology,” *International Journal of Emerging Technologies in Learning*, vol. 15, no. 5, 2021.
- [92] K. S. Fleckenstein, “Defining affect in relation to cognition: A response to susan mleod,” *Journal of Advanced Composition*, pp. 447–453, 1991.
- [93] R. House and W. H. Marg, “Dictionary. com,” *Keyword: Persistence*, 2011.
- [94] A. Bhardwaj, “Importance of education in human life: A holistic approach,” *International Journal of Science and Consciousness*, vol. 2, no. 2, pp. 23–28, 2016.
- [95] S. Koran, “The role of teachers in developing learners’ speaking skill,” in *6th International Visible Conference on Educational Studies and Applied Linguistics*, April, pp. 400–4016, 2015.
- [96] G. Falloon, M. Hatzigianni, M. Bower, A. Forbes, and M. Stevenson, “Understanding k-12 stem education: A framework for developing stem literacy,” *Journal of Science Education and Technology*, vol. 29, no. 3, pp. 369–385, 2020.
- [97] A. Ata-Aktürk and H. Ö. Demircan, “Supporting preschool children’s stem learning with parent-involved early engineering education,” *Early Childhood Education Journal*, vol. 49, no. 4, pp. 607–621, 2021.
- [98] E. A. Firat, “Science, technology, engineering, and mathematics integration: Science teachers’ perceptions and beliefs,” *Science Education International*, vol. 31, no. 1, pp. 104–116, 2020.
- [99] Y.-H. Ching, Y.-C. Hsu, and S. Baldwin, “Developing computational thinking with educational technologies for young learners,” *TechTrends*, vol. 62, no. 6, pp. 563–573, 2018.
- [100] A. Sullivan and M. U. Bers, “Dancing robots: integrating art, music, and robotics in singapore’s early childhood centers,” *International Journal of Technology and Design Education*, vol. 28, no. 2, pp. 325–346, 2018.
- [101] A.-M. Velentza, S. Ioannidis, N. Georgakopoulou, M. Shidujaman, and N. Fachantidis, “Educational robot european cross-cultural design,” in *International Conference on Human-Computer Interaction*, pp. 341–353, Springer, 2021.
- [102] W. S. Burleson, D. B. Harlow, K. J. Nilsen, K. Perlin, N. Freed, C. N. Jensen, B. Lahey, P. Lu, and K. Muldner, “Active learning environments with robotic tangibles: Children’s physical and virtual spatial programming experiences,” *IEEE Transactions on Learning Technologies*, vol. 11, no. 1, pp. 96–106, 2017.
- [103] E. M. García Terceño, I. M. Greca, A. Redfors, and M. Fridberg, “Implementation of an integrated stem activity in pre-primary schools,” in *International Conference on European Transnational Education*, pp. 30–39, Springer, 2020.
- [104] C. Wongwatkit, P. Prommool, R. Nobnob, S. Boonsamuan, and R. Suwan, “A collaborative stem project with educational mobile robot on escaping the maze: prototype design and evaluation,” in *International Conference on Web-Based Learning*, pp. 77–87, Springer, 2018.
- [105] W.-Y. Huang, C.-F. Hu, and C.-C. Wu, “The use of different kinds of robots to spark student interest in learning computational thinking,” in

- 2018 *International Conference on Learning and Teaching in Computing and Engineering (LaTICE)*, pp. 11–16, IEEE, 2018.
- [106] D. Carrillo-Zapata, C. Lee, K. M. Digumarti, S. Hauert, and C. Boushel, “Lessons from delivering a stem workshop using educational robots given language limitations,” in *International Conference on Robotics in Education (RiE)*, pp. 284–295, Springer, 2019.
- [107] J. Elizabeth Casey, P. Gill, L. Pennington, and S. V. Mireles, “Lines, roamers, and squares: Oh my! using floor robots to enhance hispanic students’ understanding of programming,” *Education and Information Technologies*, vol. 23, no. 4, pp. 1531–1546, 2018.
- [108] Y. Chicas, R. Canek, and O. Rodas, “Developing stem competences by building low-cost technology robots: A work in progress,” in *2019 IEEE Integrated STEM Education Conference (ISEC)*, pp. 379–383, IEEE, 2019.
- [109] M.-C. Yuen, K. K. Chan, and K. S. Li, “Mobile app controlled modular combat robot for stem education,” in *2021 International Conference on COMMunication Systems & NETWORKS (COMSNETS)*, pp. 64–68, IEEE, 2021.
- [110] N. Fachantidis, A. G. Dimitriou, S. Pliasa, V. Dagdilelis, D. Pnevmatikos, P. Perlantidis, and A. Papadimitriou, “Android os mobile technologies meets robotics for expandable, exchangeable, reconfigurable, educational, stem-enhancing, socializing robot,” in *Interactive Mobile Communication, Technologies and Learning*, pp. 487–497, Springer, 2017.
- [111] F.-C. O. Yang, “The design of ar-based virtual educational robotics learning system,” in *2019 8th International Congress on Advanced Applied Informatics (IIAI-AAI)*, pp. 1055–1056, IEEE, 2019.
- [112] S. M. Rahman, “Metrics and methods for evaluating learning outcomes and learner interactions in robotics-enabled stem education,” in *2020 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)*, pp. 2103–2108, IEEE, 2020.
- [113] M. Jeon, M. FakhrHosseini, J. Barnes, Z. Duford, R. Zhang, J. Ryan, and E. Vasey, “Making live theatre with multiple robots as actors bringing robots to rural schools to promote steam education for under-served students,” in *2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, pp. 445–446, IEEE, 2016.
- [114] J. Barnes, S. M. FakhrHosseini, E. Vasey, C. H. Park, and M. Jeon, “Child-robot theater: Engaging elementary students in informal steam education using robots,” *IEEE Pervasive Computing*, vol. 19, no. 1, pp. 22–31, 2020.
- [115] M. Rácz, E. Noboa, B. Détár, Á. Nemes, P. Galambos, L. Szűcs, G. Márton, G. Eigner, and T. Haidegger, “Platypous—a mobile robot platform and demonstration tool supporting stem education,” *Sensors*, vol. 22, no. 6, p. 2284, 2022.
- [116] C. Boya-Lara, D. Saavedra, A. Fehrenbach, and A. Marquez-Araque, “Development of a course based on beam robots to enhance stem learning in electrical, electronic, and mechanical domains,” *International Journal of Educational Technology in Higher Education*, vol. 19, no. 1, pp. 1–23, 2022.
- [117] A. M. Porras and J. Alfaro-Velasco, “Playing robosoccer with machine learning: A learning and teaching experience based on stem,” in *2020 15th Iberian Conference on Information Systems and Technologies (CISTI)*, pp. 1–6, IEEE, 2020.
- [118] J. Flot, R. Higashi, J. McKenna, R. Shoop, and E. Witherspoon, “Using model eliciting activities to engage students in computational thinking practices,” *Retrieved January*, vol. 22, p. 2019, 2016.
- [119] S. Zeaiter and P. Heinsch, “Robotikum: Promoting stem education in schools using an adaptive learning scenario,” in *International Conference on Robotics in Education (RiE)*, pp. 3–15, Springer, 2020.
- [120] E. A. Konijn and J. F. Hoorn, “Robot tutor and pupils’ educational ability: Teaching the times tables,” *Computers & Education*, vol. 157, p. 103970, 2020.
- [121] H.-P. Yueh, W. Lin, S.-C. Wang, and L.-C. Fu, “Reading with robot and human companions in library literacy activities: A comparison study,” *British Journal of Educational Technology*, vol. 51, no. 5, pp. 1884–1900, 2020.
- [122] L. Levinson, O. Gvirsman, I. M. Gorodesky, A. Perez, E. Gonen, and G. Gordon, “Learning in summer camp with social robots: A morphological study,” *International Journal of Social Robotics*, vol. 13, no. 5, pp. 999–1012, 2021.
- [123] R. Mohanan, C. Stringfellow, and D. Gupta, “An emotionally intelligent tutoring system,” in *2017 Computing Conference*, pp. 1099–1107, IEEE, 2017.
- [124] A. Takacs, G. Eigner, L. Kovács, I. J. Rudas, and T. Haidegger, “Teacher’s kit: Development, usability, and communities of modular robotic kits for classroom education,” *IEEE Robotics & Automation Magazine*, vol. 23, no. 2, pp. 30–39, 2016.
- [125] M. Masril, B. Hendrik, H. T. Fikri, B. Priambodo, E. Naf’an, I. Handriani, Z. P. Putra, A. K. Nseaf, *et al.*, “The effect of lego mindstorms as an innovative educational tool to develop students’ creativity skills for a creative society,” in *Journal of Physics: Conference Series*, vol. 1339, p. 012082, IOP Publishing, 2019.
- [126] L. C. Gerber, A. Calasanz-Kaiser, L. Hyman, K. Voitiuk, U. Patil, and I. H. Riedel-Kruse, “Liquid-handling lego robots and experiments for stem education and research,” *PLoS biology*, vol. 15, no. 3, p. e2001413, 2017.
- [127] H. Yi, C. Knabe, T. Pesek, and D. W. Hong, “Experiential learning in the development of a darwin-hp humanoid educational robot,” *Journal of Intelligent & Robotic Systems*, vol. 81, no. 1, pp. 41–49, 2016.
- [128] A. Nusayr and R. da Silva, “The use of educational robots to engage the youth in computer science: A case study,” in *2019 Latin American Robotics Symposium (LARS), 2019 Brazilian Symposium on Robotics (SBR) and 2019 Workshop on Robotics in Education (WRE)*, pp. 477–481, 2019.
- [129] Z. Huang, C. Lin, M. Kanai-Pak, J. Maeda, Y. Kitajima, M. Nakamura, N. Kuwahara, T. Ogata, and J. Ota, “Impact of using a robot patient for nursing skill training in patient transfer,” *IEEE Transactions on Learning Technologies*, vol. 10, no. 3, pp. 355–366, 2016.
- [130] D. Yang, E.-S. Oh, and Y. Wang, “Hybrid physical education teaching and curriculum design based on a voice interactive artificial intelligence educational robot,” *Sustainability*, vol. 12, no. 19, p. 8000, 2020.
- [131] P. Vogt, M. De Haas, C. De Jong, P. Baxter, and E. Krahmer, “Child-robot interactions for second language tutoring to preschool children,” *Frontiers in human neuroscience*, vol. 11, p. 73, 2017.
- [132] E. Chew and X. N. Chua, “Robotic chinese language tutor: personalising progress assessment and feedback or taking over your job?,” *On the Horizon*, vol. 28, no. 3, pp. 113–124, 2020.
- [133] H. Lee and J. H. Lee, “Social robots for english language teaching,” *ELT Journal*, vol. 76, no. 1, pp. 119–124, 2022.
- [134] M. Schmidt, V. Benzing, A. Wallman-Jones, M.-F. Mavilidi, D. R. Lubans, and F. Paas, “Embodied learning in the classroom: Effects on primary school children’s attention and foreign language vocabulary learning,” *Psychology of sport and exercise*, vol. 43, pp. 45–54, 2019.
- [135] D. Ziouzos, D. Rammos, T. Bratitsis, and M. Dasygenis, “Utilizing educational robotics for environmental empathy cultivation in primary schools,” *Electronics*, vol. 10, no. 19, p. 2389, 2021.
- [136] S. Müller, B. Bergande, and P. Brune, “Robot tutoring: On the feasibility of using cognitive systems as tutors in introductory programming education: A teaching experiment,” in *Proceedings of the 3rd European Conference of Software Engineering Education*, pp. 45–49, 2018.
- [137] A. Meghdari, M. Alemi, M. Zakipour, and S. A. Kashanian, “Design and realization of a sign language educational humanoid robot,” *Journal of Intelligent & Robotic Systems*, vol. 95, no. 1, pp. 3–17, 2019.
- [138] I. Giannopulu, A. Etournaud, K. Terada, M. Velonaki, and T. Watanabe, “Ordered interpersonal synchronisation in asd children via robots,” *Scientific Reports*, vol. 10, no. 1, pp. 1–10, 2020.
- [139] M. A. Al-Tae, R. Kapoor, C. Garrett, and P. Choudhary, “Acceptability of robot assistant in management of type 1 diabetes in children,” *Diabetes technology & therapeutics*, vol. 18, no. 9, pp. 551–554, 2016.
- [140] M. Shiomi, Y. Tamura, M. Kimoto, T. Iio, R. Akahane-Yamada, and K. Shimohara, “Two is better than one: verification of the effect of praise from two robots on pre-school children’s learning time,” *Advanced Robotics*, vol. 35, no. 19, pp. 1132–1144, 2021.
- [141] I. M. Verner, A. Polishuk, and N. Krayner, “Science class with robotics: using a robot teacher to make science fun and engage students,” *IEEE Robotics & Automation Magazine*, vol. 23, no. 2, pp. 74–80, 2016.
- [142] L. M. d. Nascimento, D. S. Neri, T. d. N. Ferreira, F. d. A. Pereira, E. A. Y. Albuquerque, L. M. G. Gonçalves, and S. T. d. L. Sá, “Sbotics-gamified framework for educational robotics,” *Journal of Intelligent & Robotic Systems*, vol. 102, no. 1, pp. 1–20, 2021.
- [143] J. Leonard, A. Buss, R. Gamboa, M. Mitchell, O. S. Fashola, T. Hubert, and S. Almuhyirah, “Using robotics and game design to enhance children’s self-efficacy, stem attitudes, and computational thinking skills,” *Journal of Science Education and Technology*, vol. 25, no. 6, pp. 860–876, 2016.
- [144] S. Schez-Sobrino, D. Vallejo, C. Glez-Morcillo, M. Á. Redondo, and J. J. Castro-Schez, “Robotic: A serious game based on augmented reality for learning programming,” *Multimedia Tools and Applications*, vol. 79, no. 45, pp. 34079–34099, 2020.
- [145] A. Karademir and B. Yıldırım, “A different perspective on preschool stem education: Preschool stem education and engineering for preservice teachers,” *Journal of Turkish Science Education*, vol. 18, no. 3, pp. 338–350, 2021.

- [146] J. Hallström and K. J. Schönborn, "Models and modelling for authentic stem education: Reinforcing the argument," *International Journal of STEM Education*, vol. 6, no. 1, pp. 1–10, 2019.
- [147] L. D. English, "Stem education k-12: Perspectives on integration," *International Journal of STEM education*, vol. 3, no. 1, pp. 1–8, 2016.
- [148] M. Bacovic, Z. Andrijasevic, and B. Pejovic, "Stem education and growth in europe," *Journal of the Knowledge Economy*, vol. 13, no. 3, pp. 2348–2371, 2022.
- [149] M. Fridin, "Storytelling by a kindergarten social assistive robot: A tool for constructive learning in preschool education," *Computers & education*, vol. 70, pp. 53–64, 2014.
- [150] A.-M. Velentza, S. Ioannidis, N. Georgakopoulou, M. Shidujaman, and N. Fachantidis, "Educational robot european cross-cultural design," in *International Conference on Human-Computer Interaction*, pp. 341–353, Springer, 2021.
- [151] Z. Pei and Y. Nie, "Educational robots: Classification, characteristics, application areas and problems," in *2018 Seventh International Conference of Educational Innovation through Technology (EITT)*, pp. 57–62, IEEE, 2018.
- [152] T. Nomura and T. Suzuki, "Relationships between humans' gender conception, expected gender appearances, and the roles of robots: A survey in japan," *International Journal of Social Robotics*, vol. 14, no. 5, pp. 1311–1321, 2022.
- [153] N. A. Espinoza E, R. P. Almeida G, L. Escobar, and D. Loza, "Development of a social robot nar for children's education," in *Advances in Emerging Trends and Technologies: Volume 2*, pp. 357–368, Springer, 2020.
- [154] J. López-Belmonte, A. Segura-Robles, A.-J. Moreno-Guerrero, and M.-E. Parra-González, "Robotics in education: a scientific mapping of the literature in web of science," *Electronics*, vol. 10, no. 3, p. 291, 2021.
- [155] B. S. Childs, M. D. Manganiello, and R. Korets, "Novel education and simulation tools in urologic training," *Current urology reports*, vol. 20, pp. 1–8, 2019.
- [156] A. Goel, "Ai education for the world," *AI magazine*, vol. 38, no. 2, pp. 3–4, 2017.
- [157] D. Touretzky, C. Gardner-McCune, C. Breazeal, F. Martin, and D. Seehorn, "A year in k-12 ai education," *AI Magazine*, vol. 40, no. 4, pp. 88–90, 2019.
- [158] X. Yang, "Accelerated move for ai education in china," *ECNU Review of Education*, vol. 2, no. 3, pp. 347–352, 2019.
- [159] S. Anwar, N. A. Bascou, M. Menekse, and A. Kardgar, "A systematic review of studies on educational robotics," *Journal of Pre-College Engineering Education Research (J-PEER)*, vol. 9, no. 2, p. 2, 2019.
- [160] A. Paiva, S. Mascarenhas, S. Petisca, F. Correia, and P. Alves-Oliveira, "Towards more humane machines: Creating emotional social robots," pp. 125–139, 2018.
- [161] I. Leite, C. Martinho, and A. Paiva, "Social robots for long-term interaction: a survey," *International Journal of Social Robotics*, vol. 5, pp. 291–308, 2013.
- [162] J. W. Hostetter, C. Conati, X. Yang, M. Abdelshiheed, T. Barnes, and M. Chi, "Xai to increase the effectiveness of an intelligent pedagogical agent," in *Proceedings of the 23rd ACM International Conference on Intelligent Virtual Agents*, pp. 1–9, 2023.
- [163] S. Rahimi, "Extended mind, embedded ai, and" the barrier of meaning," in *AAAI Spring Symposium: Interpretable AI for Well-being*, 2019.
- [164] J. Wang, "Should we develop empathy for social robots?," *Sex robots: Social impact and the future of human relations*, pp. 41–55, 2021.
- [165] J. R. Saura, D. Palacios-Marqués, and A. Iturricha-Fernández, "Ethical design in social media: Assessing the main performance measurements of user online behavior modification," *Journal of Business Research*, vol. 129, pp. 271–281, 2021.
- [166] D. Messer, L. Thomas, A. Holliman, and N. Kucirkova, "Evaluating the effectiveness of an educational programming intervention on children's mathematics skills, spatial awareness and working memory," *Education and Information Technologies*, vol. 23, pp. 2879–2888, 2018.
- [167] C. Lytridis, E. Vrochidou, S. Chatzistamatis, and V. Kaburlasos, "Social engagement interaction games between children with autism and humanoid robot nao," in *International Joint Conference SOCO'18-CISIS'18-ICEUTE'18: San Sebastián, Spain, June 6-8, 2018 Proceedings 13*, pp. 562–570, Springer, 2019.
- [168] E. Silva, "Measuring skills for 21st-century learning," *Phi delta kappan*, vol. 90, no. 9, pp. 630–634, 2009.
- [169] S. Spaulding, "Personalized robot tutors that learn from multimodal data," in *Proceedings of the 17th International Conference on Autonomous Agents and MultiAgent Systems*, pp. 1781–1783, 2018.
- [170] M. Chen, F. Liu, and Y.-H. Lee, "My tutor is an ai: The effects of involvement and tutor type on perceived quality, perceived credibility, and use intention," in *International Conference on Human-Computer Interaction*, pp. 232–244, Springer, 2022.
- [171] S. Al Moubayed, J. Beskow, B. Bollepalli, A. Hussien-Abdelaziz, M. Johansson, M. Koutsombogera, J. D. Lopes, J. Novikova, C. Oertel, G. Skantze, et al., "Tutoring robots: Multiparty multimodal social dialogue with an embodied tutor," in *Innovative and Creative Developments in Multimodal Interaction Systems: 9th IFIP WG 5.5 International Summer Workshop on Multimodal Interfaces, eINTERFACE 2013, Lisbon, Portugal, July 15–August 9, 2013. Proceedings 9*, pp. 80–113, Springer, 2014.
- [172] J. Wang, *Robotics Educational Activity Design Under the View of Integration of STEM Discipline*. PhD thesis, Wenzhou University, 2014.
- [173] Y. Sun, *The Research and Development of Robotics Curriculum in Elementary Education*. PhD thesis, Capital Normal University, 2006.
- [174] S. Chookaew, S. Howimanporn, P. Pratumswan, S. Hutamarn, W. Sootkaneung, and C. Wongwatkit, "Enhancing high-school students' computational thinking with educational robotics learning," in *2018 7th International Congress on Advanced Applied Informatics (IIAI-AAI)*, pp. 204–208, IEEE, 2018.
- [175] Z. Zhong, *A Framework of Instructional Design Toward Knowledge Age: Promoting the Development of the Learner*. PhD thesis, East China Normal University, 2004.
- [176] S. Y. Sun, W. W. Xu, Z. H. Li, K.-K. Ng, and I. K.-W. Lai, "A study on the appearances and functionalities of education robots for attracting students' attention and interactive interests," in *2018 International Symposium on Educational Technology (ISET)*, pp. 245–249, IEEE.
- [177] T. Matsui and S. Yamada, "The design method of the virtual teacher," in *Proceedings of the 7th International Conference on Human-Agent Interaction*, pp. 97–101.
- [178] M. Alemi, A. Meghdari, and M. Ghazisaedy, "Employing humanoid robots for teaching english language in iranian junior high-schools," *International Journal of Humanoid Robotics*, vol. 11, no. 03, p. 1450022, 2014.

Xinyue Zhang is currently pursuing a Ph.D. degree in AI for Education at East China Normal University under the supervision of Professor Guitao Cao. Her research interests include visual sentiment recognition, and AI in education.



Fangqing Zhu received the B.S. degree in educational technology from Beijing Normal University, China, in 2021. She is now pursuing the M.S. degree in education information technology at East China Normal University, China. Her current research interest focuses on AI in education.





Kun Wang received the B.A. degree from Hunan Agricultural University. He is currently pursuing his master degree at East China Normal University. His interests include educational technology and AI in education.



Guitao Cao obtained her Ph.D. in 2006 from Shanghai Jiao Tong University with a focus on pattern recognition. She is currently a professor of Software Engineering Institute, East China Normal University (ECNU), Shanghai. ECNU is the top tier university in China with a high rank (Level A) in Software Engineering in China. She was also a visiting researcher with University of Missouri at Columbia. She has published decades of peer reviewed papers in top venues including IEEE Transactions on Cybernetics, IEEE Transactions on Multimedia, and

IEEE Transactions on Biomedical Engineering. Prof. Cao is also the Principal Investigator for many research funding with major sponsors including the National Science Foundation of China, Ministry of Industry and Information Technology of the People's Republic of China, and Science Foundation of Shanghai. She is a technical committee member of Embedded System of China Computer Federation, and a member of IEEE. Her research interests include machine learning and its application in education, image understanding and analysis, and edge computing.



Yaofeng Xue received the B.S., M.S. degrees from Shenyang University of Chemical Technology in 2000, 2003, respectively, and the Ph.D. degree from Shanghai Jiao Tong University in 2008. He is currently an Associate Professor in Shanghai Engineering Research Center of Digital Educational Equipment, Department of Education Information Technology, and Key Laboratory of Advanced Theory and Application in Statistics and Data Science - MOE, East China Normal University. His research interests are in the area of Artificial Intelligence in

Education, STEM Education and Virtual Reality.



Mingzhuo Liu Ph.D. in Instructional Technology, Professor, Doctoral Supervisor, School of Open Learning and Education, East China Normal University, Shanghai, China. Research Interests: Online Education, Digital Learning and Pedagogical Usability.