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# What would the matrix do?: a systematic review of K-12 AI learning contexts and learner-interface interactions

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**ABSTRACT**
This systematic review examines the empirical literature published between 2014 and 2021 that situates artificial intelligence within K-12 educational contexts. Our review synthesizes 12 articles and highlights artificial intelligence's instructional contexts and applications in K-12 learning environments. We focused our synthesis on the learning contexts and the learner-interface interactions. Our findings highlight that most of intelligent systems are being deployed in math or informal settings. Also, there are opportunities for more collaboration to facilitate teaching and learning in domain-specific areas. Additionally, researchers can explore how to implement more collaborative learning opportunities between intelligent tutors and learners. We conclude with a discussion of the reciprocal nature of this technology integration.

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In our technology-driven society, technology is continually being integrated into more aspects of our lives. This integration has increased exponentially in response to the global COVID-19 pandemic (Adedoyin & Soykan, 2020; Brenan, 2020; Kohnke & Moorhouse, 2022; Moore, 2020; Roitsch et al., 2021). In particular, artificial intelligence has allowed for more robust technology integration. Canziani and MacSween (2021) estimate that 60 million Americans aged 18 or older have at least two smart home devices. These devices may facilitate tasks through speech recognition and language understanding (e.g., locking the door, adjusting music volume, answering factual questions, etc.). Beyond the home, AI-based systems utilize computer vision to allow self-driving cars to sense when to change lanes or identify road hazards.

Within the STEM workforce, scientists regularly use AI systems in their scientific practices to investigate society's understanding of natural systems. Innovations in AI have allowed scientists to collect new data, re-analyze old data using new methods, and expand how we look at the world around us. Bondi et al. (2018) sought to combat poachers' deadly challenges to wildlife by using uncrewed aerial vehicles to detect the thermal presence of poachers and notify park rangers before animals were at risk. AI lends itself to multiple disciplines whether in the background of our lives through devices, more intentionally at work, or integrated within lessons during K-12 instruction.

With the growing reliance on technology, it is essential that students are exposed to and taught how to effectively use technology early to succeed in the real world (Ozerbas & Erdogan, 2017). When discussing AI in the K-12 educational context, scholars typically refer to machine learning (ML). Greener et al. (2022) definition of ML emphasizes the relationship between using computers to simulate human behavior to expand knowledge in a specific domain. In addition, ML aims to address how computer systems can self-improve without human intervention (Jordan

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& Mitchell, 2015). In an educational context, how can a machine create a better experience for students and assist them in reaching their learning objectives?

The potential of AI, specifically ML, in K-12 education is vast. These technologies can revolutionize students' learning by providing instant feedback, personalized content, and data-driven insights (Anderson et al., 1995). Additionally, AI, specifically ML, can help educators identify and address learning gaps more quickly and effectively. Ultimately, these technologies have the potential to improve student outcomes by providing a more customized and effective learning experience. However, it is essential to note that these technologies are still in their infancy, and it will likely be several years before they are widely adopted in K-12 education (Rosé, 2017).

The literature review section presents prior literature reviews focused on integrating machine learning in K-12 education. Our methods section uses PRISMA (Liberati et al., 2009) to document how we identified articles for this study. We share the key findings on these themes, and their contributions are summarized in the results and discussion sections. Finally, the paper discusses the reciprocal perspectives on AI and human intelligence in education.

## Literature review

Machine learning has been implemented in various K-12 educational contexts. Chen et al. (2020) systematically analyzed influential artificial intelligence in highly cited educational scientific articles between 1999 and 2019. Their analysis found a rise in texts focusing on the implementation and value of AI tools and resources in education since 2001, especially in online environments. When considering the keywords for the included texts, Chen et al. found that machine learning, artificial intelligence, tutoring system/intelligent tutoring system, neural network, and learning technique were most prevalent. Chen et al. posited that there is still work to be done in multiple areas of integrating AI in K-12 education (e.g., implementing deep learning technologies and advanced AI methods).

Sanusi et al. (2021) conducted a systematic review of curated ML learning tools supporting K-12 teachers in deciding which systems make the most sense for their classrooms. Sanusi and colleagues organized their findings based on whether the ML system was a conversational agent (eight found), programming environment (eight found), robotic (four found), or unplugged activity (six found). Su and Yang (2022) focused their scoping review on AI-assisted learning and development in early childhood education (preschool to kindergarten). Their analysis of 17 texts from 1995 – 2021 demonstrated that several tools have effectively taught machine learning concepts to students ages three through eight. Also, the integration of AI concepts into the early childhood education curriculum was shown to strengthen "creativity, emotional control, collaborative inquiry, literacy skills, and computational thinking…[and] enthusiasm" (Su & Yang, 2022). Su and Yang (2022) concluded that one of the approaches to utilizing AI for very young students is through tutoring systems. There is extensive research on this tool for older students, but research is lacking in early childhood education.

Within the K-12 context, adaptive learning systems provide opportunities for machine learning integration. In their systematic review of adaptive learning systems, Martin et al. (2020) found that 26% of the included studies were situated in K-12 contexts. Adaptive systems can provide differentiated instruction and empower learners to participate in their learning actively (Kumar et al., 2017; Martin et al., 2020; Normadhi et al., 2019). For example, many educational technology researchers develop intelligent tutoring systems (ITS) which lend themselves to multiple courses, including but not limited to math, science, and computer science. An ITS allows for combining AI techniques with educational methods (Mousavinasab et al., 2021). The vital feature of these systems is the ability to customize instructional activities and strategies based on the learner's characteristics and needs. ITS can address the lack of time teachers have to provide individualized feedback for each learner. Gupta and Sabitha (2019) investigated the causes of students dropping out of massive online open courses (MOOC) and found that lack of interaction was one of the four primary reasons. Scholars continue to develop ITS to alleviate the burden on teachers. These measures are meant to supplement teachers' classroom presence by providing more opportunities for student interaction (Moore, 2016; Moore & Miller, 2022). A variety of machine learning systems have been implemented in K-12 spaces. Many of these use ITS to scaffold instruction to make the information accessible to students. One example of this includes Graesser's (2016) use of Autotutor, an ITS that adjusts the content trajectory based on a student's affective state. Similarly, Taub and Azevedo (2019) explored how an ITS can support metacognitive skill development. Vittorini et al. (2021) found that implementation of ITS extends from dynamic and social cognitive supports for students to evaluating/grading assistants for educators and sociocultural ITS that inform and guide users about learning-by-teaching unwritten cultural rules (Mohammed & Mohan, 2015).

Another aspect of machine learning in K-12 that is starting to receive attention is game-based learning. There is a significant opportunity for learning at the intersection of gaming and ML as games may be more likely to engage students ages four to eighteen (Author et al., 2021b). Giannakos et al. (2020) reviewed 17 AI/ML gaming applications and found that many fall into the computer science discipline with a focus on coding. The prevalence of computer science contexts highlighted by Giannakos et al. (2020) aligns with similar adaptive learning findings by Martin et al. (2020). ViPER introduces middle school students to machine learning concepts as they guide a robot across a determined journey in space (Parker & Becker, 2014). The gamification of learning ML systems supports students in thinking in new ways about the world around them. In Thailand, Sakulkueakulsuk et al. (2018) explored how a game could empower middle schoolers to learn ML agricultural-related skills. In this case, students were training the machine based on the condition or ripeness of mangoes. Ultimately, the machine-classified mangoes were sent to a market auction where students earned points based on how well the machine performed the task.

## Purpose

This systematic review aims to synthesize the salient literature around the use of artificial intelligence in K-12 educational contexts. Along with the recent research focused on AI in K-12 education, this paper aims to identify ML implementation trends. There has been a large body of research around artificial intelligence but less specifically on K-12 contexts. We endeavored to synthesize this research to provide insight into current trends and help identify future research directions. Our guiding research questions were:

1. What is the current state of research on machine intelligence in K-12 educational contexts?
2. In what waysis machine intelligence supporting teaching and learning?

## Methods

To answer our research questions, we conducted a systematic review of empirical-based peer-review journal articles that answered the research questions (Arksey & O'Malley, 2005). We implemented the PRISMA guidelines (Liberati et al., 2009), and our process is shown in Figure 1. The use of PRISMA creates transparency in our process, as PRISMA is an established process that allows for replication or updates to this review (Page et al., 2021).

### *Search*

We conducted a boolean/phrase search in Academic Search Premier and Education Source using the following search strings "("develop"*" OR ""design"*" OR ""evaluat*") AND "("interface"*") AND "("AI"" OR ""artificial intelligence"" OR ""machine intelligence"" OR ""machine learning"" OR ""intelligent tutoring system"*"). The "*" is the wildcard search character. These search terms

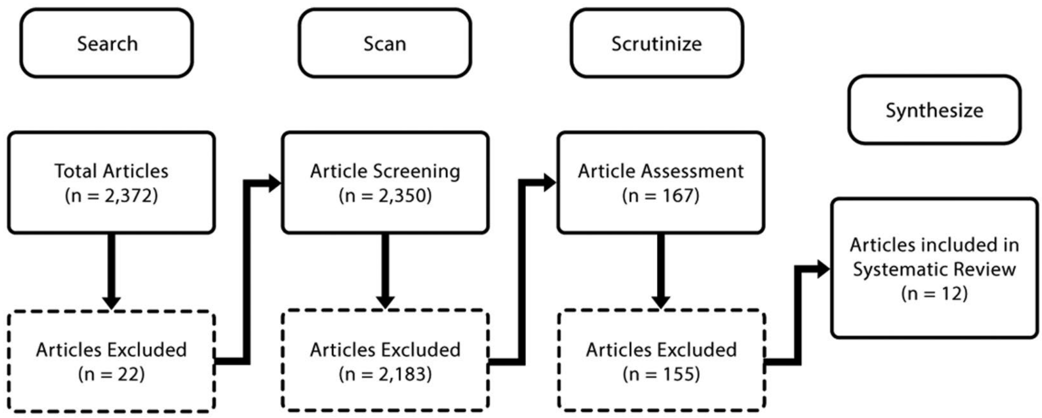


**Figure 1.** Article selection process. Adapted from Liberati et al. (2009).

**Table 1.** Inclusion and exclusion criteria.

| Inclusion criteria | Exclusion Criteria |
|---|---|
| Peer-reviewed article in Q1 or Q2 journal* | Article was book chapter, conference proceeding, dissertation or not peer-reviewed |
| Published between 2014-2021 in English | Article was not empirical |
| Article focused on K-12 educational context | |
| Article utilized artificial intelligence | |
| Article addressed learning contexts, learning support or learner-interface interactions | |

**Note: Used SciImago (https://www.scimagojr.com/journalrank.php) to determine journal quartile.*

were used as they were the most relevant and specific to our research question. While other search terms could be useful, they may be too vague or too specific and may return many irrelevant results or results focusing on one specific area. This search strategy might have overlooked some studies that used discipline-specific terms to describe intelligent systems. We further limited our search results to empirical peer-reviewed English articles published between 2014 and 2021. We did not include 'K-12' as a search term, because that specific term is only used in the United States and some European countries. Instead, we narrowed it down to the K-12 context through manual scanning. We aimed to identify articles in the K-12 educational context, but since we did not know how the context would be identified, we expanded our search strings as broadly as possible. This initial query yielded 2,372 results, and we removed 22 duplicates.

## Scan

We used the abstracts to narrow the pool to articles focused on K-12 educational contexts. The broad search terms ensured that we would capture as many articles as possible. After scanning the abstracts, we removed 2,183 for irrelevance, leaving us with 167 to scrutinize.

## Scrutinize

In this phase, the first two authors read each article and determined their fit based on the inclusion and exclusion criteria (Table 1). We wanted to ensure that high-quality articles were included in the final synthesis, so we reviewed each journal to ensure they were listed in SCImago (https://www.scimagojr.com/journalrank.php) and either a Q1 or Q2 journal. This filtering by journal type has been used in other systematic reviews to ensure the quality of included studies (Bano et al., 2018; Moore, 2020). This criterion removed 29 articles. We next checked for the context of the study and determined that 77 were not primarily focused on

K-12 contexts. We removed 25 because they did not focus on artificial intelligence, and another 24 were not empirical-based studies. We removed 155 articles based on our inclusion and exclusion criteria, resulting in the 12 studies included.

## Synthesize

After completing our process, 12 articles met our criteria. In the subsequent sections, we synthesize our findings.

## Results and discussion

### *RQ1: What is the current state of research on machine intelligence in K-12 educational contexts?*

This section includes descriptive information on the publication dates, grade level, and content areas for machine intelligence in K-12 contexts. We then present the formal and informal learning contexts and learner-interface interactions discussed in our studies.

### *Publication dates and contexts*

Between 2014 and 2021, we found that 2020 was the only year that did not have a published article, with 2014 having the most articles (Figure 2).

In some of the articles, the authors explicitly stated the subject area. In those articles, we found that math was the most common subject area, followed by science and language arts. Elementary school contexts were the most common for our included studies, and we saw articles including broad ranges from kindergarten through adults (Table 2).

### *Formal and informal learning contexts*

Articles discussed both formal and informal learning contexts (Table 3).

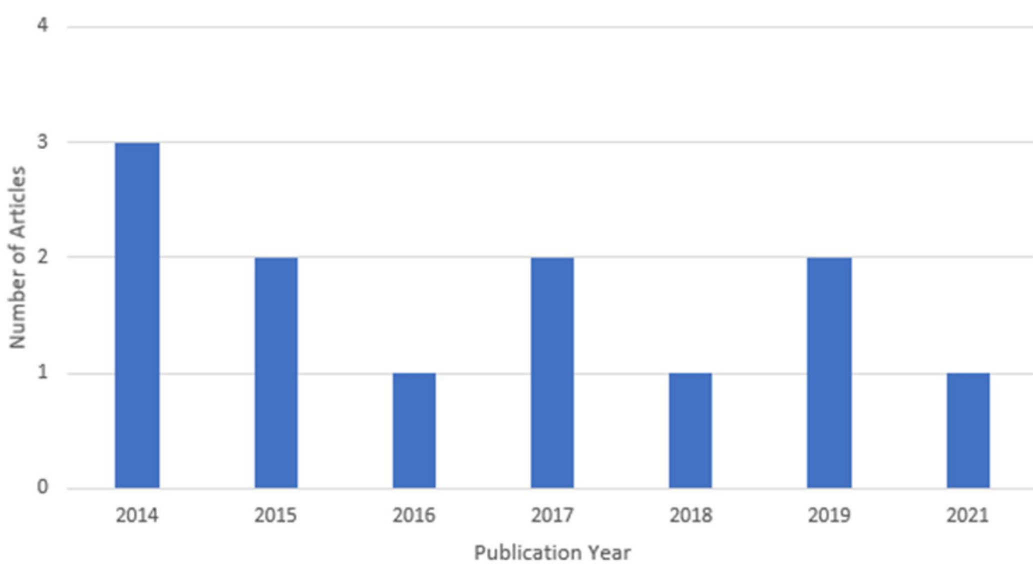


**Figure 2.** Articles by publication year.

**Table 2.** Articles by grade level.

| Grade Level | Articles |
|---|---|
| Kindergarten | (Kewalramani et al., 2021) |
| Elementary School (K – Grade 6) | (Chu et al., 2014; Kaya et al., 2017; Rau et al., 2014) |
| Elementary and Middle School | (Meyer & Wijekumar, 2014) |
| Middle School (Grades 7-8) | (Kautzmann & Jaques, 2019; Li et al., 2015) |
| High School (Grades 9-12) | (Bringula et al., 2016; Hossain et al., 2018) |
| Broad ranges | (Confalonieri et al., 2015; Gonzalez et al., 2017; Noroozi et al., 2019) |

**Table 3.** Articles by learning context.

| Contexts | Articles |
|---|---|
| Formal learning contexts | (Hossain et al., 2018; Kautzmann & Jaques, 2019; Kaya et al., 2017) |
| Informal learning contexts | (Confalonieri et al., 2015; Gonzalez et al., 2017) |

Using technology to allow for dynamic interaction with students can be integrated into formal learning contexts. Kautzmann and Jaques (2019) studied the use of a pedagogical avatar that interacted with learners and fostered the metacognitive processes of 8$^{th}$-grade students. The focus of this study was how the computer-based learning environment could adapt and support students' emotional regulation and learning. Hossain et al. (2018) explored inquiry-based learning of middle school biology students by adapting the Open EdX online learning platform. The open-learning platform allowed for diverse participants, and 46 countries were included in their evaluation sample. In this study, technology was used to integrate diverse perspectives in the interactive biology lab. Kaya et al. (2017) study explored using machine learning techniques to analyze speech patterns of Russian children aged 3 to 7 years old and automatically detect emotional states.

Learning can also happen in informal contexts, and we found that two of the 12 studies focused on these informal learning spaces (Confalonieri et al., 2015; Gonzalez et al., 2017). Both of these studies were situated in museum settings. Gonzalez et al. (2017) study was designed for middle school students and sought to use a museum exhibit about Alan Turing to spark interest in STEM education, specifically artificial intelligence and computer science. Students could use adaptive animated avatars in this interactive exhibit to engage in the Turing Test. Confalonieri et al. (2015) had a broader target age range as their study focused on using the WeCurate tool to allow multiuser interactions to engage with museum artifacts in a digital environment. The collaborative tool allowed patrons in different physical locations and at differing times to engage with the same artifact and co-construct knowledge toward making decisions regarding the museum's collection. The interface's complexity limited younger children's unsupervised participation without their parents' aid. While these studies showed the promise of bringing AI technologies into informal learning spaces, more efforts should be devoted to exploring the affordances and constraints of using AI technologies in other settings (e.g., libraries) and strategies for bridging formal and informal learning.

### *Learner-interface interaction: Intelligent agents' diverse roles*

Intelligent agents were positioned in different roles in learner-interface interaction. The roles included student, teacher, teaching assistant, and learning assistant (Table 4).

In learning-by-teaching ITS, learners are the tutors and guide a simulated student, or intelligent agent, to solve problems. The simulated student could interact with learners by asking questions and requesting hints. For example, Bringula et al. (2016) examined the impact of students' prior knowledge in mathematics on how they tutored an interactive machine-learning agent, SimStudent, to solve problems using the tutoring interface built on the web browser CTAT (Matsuda et al., 2015). SimStudent learns cognitive skills sufficient to solve the exact problems tutored and generalizes those skills to solve similar problems. Differently, Li et al. (2015) presented an intelligent system with a natural language interface where middle school students

**Table 4.** Articles by intelligent agents' roles.

| Roles | Articles |
|---|---|
| Student | (Bringula et al., 2016) |
| Teacher | (Li et al., 2015) |
| Teaching Assistant | (Chu et al., 2014) |
| Learning Assistant | (Chu et al., 2014; Meyer and Wijekumar; 2014) |

could ask agents to solve math problems. The agent would offer step-by-step solutions and summarize key concepts in the solution. This represents agents that serve as teachers who help students to gain disciplinary knowledge.

In Chu et al. (2014) study, learners received an automated diagnosis report when answering fraction questions incorrectly regarding agents as teaching and learning assistants. The report was generated by a Model-Tracing Intelligent Tutor, which identified misconceptions by tracing students' step-by-step mathematical problem-solving. The study demonstrated that this report could help teachers understand students' learning status and assist teachers in making instructional moves (e.g., leading whole-classroom discussions based on common misconceptions in the diagnosis report). Meyer and Wijekumar (2014) investigated middle school students' off-task behaviors in a web-based reading comprehension tutor environment as an example of a learning assistant. An intelligent tutor provided feedback to students while they walked through reading tasks. The authors examined the characteristics of off-task behaviors by using classification and decision tree analyses. The analyses showed that students' off-task behaviors could be explained by their motivation, reading skills, and goal orientation. Specific feedback was generated based on factors that contribute to off-task behaviors. The feedback was set up to align with learners' learning progress, such as "let's move on to the next page" and "your answer is incorrect."

The roles of agents in Gonzalez et al. (2017) and Kewalramani et al. (2021) studies are unclear. They were used as learning materials to support the development of STEM interests and inquiry literacy. Gonzalez et al. (2017) designed animated avatars to communicate with students, and after the communication, students were asked whether the avatars were real humans via video conference. The activity was designed to promote students' interest in computer science and artificial intelligence. In Kewalramani et al. (2021) study, children aged four to five played with different robotic toys (e.g., Botley, Beebots, Coji, and Qobo). Each toy has additional features that children can interact with. For example, Botley and Beebots can be programmed to walk specific paths. While children were playing with these toys, they built ramps and roadways for their robots to travel. They also interacted with Coji (i.e., an AI-interfaced robot that dances, laughs, and shows emotions) and created stories and tasks for Coji to perform. After the children completed the playing, they had whole-class discussions to foster inquiry literacy (e.g., asking questions). We can see that intelligent agents played different roles, and these roles afforded unique interactions between users and agents.

### *RQ2: in what ways is machine intelligence supporting teaching and learning?*

These studies reported findings about the affordances and constraints of AI technologies in teaching, including effects on learning gains and students' learning characteristics. Li et al. (2015) demonstrated that their algebra and geometry tutoring system worked better than human tutors by conducting a quasi-experimental study. Specifically, students were randomly assigned into two groups: one group finished homework using the tutoring system, and the other group completed homework under the guidance of human tutors (usually their parents). They explained that the quality of human tutoring mattered, and the result did not support claims that the tutoring system guarantees better learning gain in other contexts.

Similarly, Rau et al. (2014) investigated the math learning effect of demonstrating interleaving tasks with multiple representations in an intelligent tutoring system, Fractions Tutor. This system supported students' fraction knowledge acquisition by presenting multiple interactive graphical representations. Unlike Li et al.'s (2015) study, this study compared learning effects in four different conditions: blocked, fully interleaved, moderately interleaved, and increasingly interleaved. In these conditions, students could switch representations after answering a certain number of questions. For example, students in the blocked condition were allowed to switch representations after answering 36 questions, whereas students in the fully interleaved condition could switch after each question. Students walked through the same sequence of tasks and questions (e.g., developing a graphical representation for a given fraction). Analyzing students' pre- and post-tests revealed that students in interleaved conditions significantly outperformed the blocked condition. Students learning gains in the fully interleaved condition were more consistent than students in other conditions. This study contributes to the literature by demonstrating the effectiveness of interleaved practices with multiple representations in the context of elementary school fraction learning.

Bringula et al. (2016) study fell in the category of examining students' learning characteristics in intelligent tutoring systems. This study showed that prior knowledge in mathematics, particularly term identification, significantly influenced how learners interacted with the intelligent system, SimStudent. Learners with higher prior knowledge in term identification spent more time tutoring the simulated student, conducted more quizzes and requested more hints. Based on these findings, the authors called for more efforts in designing tutoring systems that meet individual students' needs by considering their backgrounds, interests, and prior knowledge.

Noroozi et al. (2019) study present the potential of learning analytics systems in supporting teaching and learning based on researchers' evaluations. This study suggestssimplified methods to analyze multimodal data with SLAM-KIT (i.e., strategic regulation of learning through learning analytics and mobile clouds for individual and collaborative learning success). This study aimed to present different ways to simplify and analyze rich multimodal data collected from collaborative learning environments using SLAM-KIT. They used multimodal data from advanced high school physics collaborative learning tasks, including 101 hours of video data, 266 million sensor data points, and 236 thousand log data entries. They examined this data using different analytic techniques in SLAM-KIT to identify phenomena related to students' activities (e.g., changes in their heart rate and body temperature). In this analysis, SLAM-KIT provided a unified and navigable overview of the interaction situation by merging multiple data sources. Evaluations from researchers showed that this system was promising to support real-time teaching and learning support, leveraging multimodal data. The research team aimed to improve the tool for teachers and students in the future.

### *Reciprocal perspectives on AI and human intelligence in education*

This review indicates a lack of intelligent systems in other disciplines beyond math and contexts in informal settings. One reason that machine intelligence has not been widely used in out-of-school settings is the lack of data for building predictive models, which has been a challenge in machine learning. However, with the increasing use of mobile devices and the rapid development of big data technologies, there are now many opportunities for collecting data in out-of-school settings. Artificial intelligence researchers should pay more attention to these opportunities and develop effective intelligent systems for informal settings. Furthermore, findings from math education in formal contexts set a solid empirical and theoretical foundation for expanding the scope of research and practice on machine intelligence in other disciplines and contexts. When transforming these findings, we should recognize that each field has challenges (e.g., helping students learn how to solve fraction problems in Rau et al. (2014) study). Close interdisciplinary collaborations between computer scientists and educators in specific domains (e.g., science) could advance research in identifying fundamental problems and generating innovative solutions to leverage machine intelligence's power in different disciplines and contexts. It would also be helpful for artificial intelligence researchers to partner with educators to develop intelligent systems that can facilitate teaching and learn in their respective disciplines and contexts.

In the reviewed studies, scholars conceptualized different roles (e.g., tutor and student) that machine intelligence can play in supporting teaching and learning. Researchers could consider roles beyond serving as a tutor or being tutored, such as learning partners and co-inquiries (Jiang et al., 2022). Emerging studies have explored designing learning environments where students and agents offer each other advice and feedback in collaborative learning (Madaio et al., 2017). A fertile area for future studies is designing agents having dynamic roles and studying how to best support student learning in role changing. This strategy is similar to how teachers change their positions when interacting with students, such as being careful listeners when students share ideas and being knowledge experts when students have misconceptions.

Moreover, future studies should explore how frequently agents should intervene and interact with users instead of assuming that the mere appearance of agents guarantees better support, particularly in collaborative learning settings (Sankaranarayanan et al., 2020). In addition, researchers should consider the design of the agent's personality. In the reviewed studies, researchers considered the personality of agents in terms of the agent's visual and verbal behavior. However, we argue that researchers might also consider the agent's personality regarding the agent's relationship with the user. The personality of agents may include the agent's role, such as a tutor, coach, or expert, and the way the agent interacts with the user, such as being encouraging, showing empathy, and communicating politely. Future studies could further explore how agent personality affects user learning and engagement.

The review showed that some benefits of AI in the learning process include: helping students learn more effectively by providing personalized feedback and recommendations, identifying students who are struggling and providing them with extra support, making the learning process more efficient by automating tasks such as grading and giving feedback and creating engaging and interactive learning experiences. However, due to the limited number of studies and relatively small sample sizes, the generalizability of the findings and long-term effects of intelligent systems in different disciplines beyond math are not well understood. Future studies should use large-scale and long-term designs to study the effects of intelligent systems in various disciplines and contexts. Furthermore, more efforts should be devoted to investigating how AI can support social and emotional learning (in addition to a well-studied area of cognitive learning) and how to use AI to create more culturally relevant learning experiences (Ladson-Billings, 1995).

Our study found that unpacking the effects of intelligent systems on teaching has not received sufficient scholarly attention. An emerging area of study is designing teacher-AI co-orchestration systems to support real-time classroom intervention (Olsen et al., 2021). Olsen et al. (2021) argue that it is essential for the field to understand how the responsibility of managing a learning scenario can be shared across multiple agents, including both teachers and AI agents. They suggested that teachers make final decisions and AI agents provide reliable information to enrich and support teachers in making such decisions. However, AI agents make mistakes; thus, teachers should be aware of this possibility during decision-making processes. In addition, it would be beneficial for future research to examine designing intelligent systems to support teacher education, such as learning how to create solid lesson plans (Poitras et al., 2019) and helping teachers to engage with simulated students from different backgrounds to raise their awareness of cultural differences and inclusive teaching (Caglar-Ozhan et al., 2022).

Some reviewed studies demonstrated that students' prior knowledge impacted how they interacted with intelligent agents (e.g., Bringula et al., 2016). We call for more rigorous studies examining how students from different backgrounds use AI technologies. There are tensions (Enyedy & Mukhopadhyay, 2007) when using intelligent systems, such as students' resistance (Sever & Guven, 2014) to AI technologies identifying prospective students for college admission. Also, in some cases, students might not trust results from machine intelligence. We should be aware of the tension, resistance, and skepticism and examine how to address such issues and turn them into opportunities for learning. In particular, we should pay close attention to these issues when involving young children, as they tend to build relationships with agents, especially those simulating human faces and voices (H. Chen et al., 2020). Researchers should devote more attention to extra-cognitive factors (e.g., students' motivation, attitudes, and prior knowledge) that can affect students' engagement, learning, and use of intelligent systems.

Researchers in learning analytics (LA) are exploring opportunities to build next-generation analysis models for practical use, such as supporting real-time classroom teaching (Noroozi et al., 2019). Technologies in the reviewed studies involve LA techniques for building predictive models to provide real-time support. However, moving from analysis to real-time support faces multiple challenges for many LA research teams (Blackmon & Moore, 2020; Moore, Rosé, 2017). One major challenge is balancing simplifying models for real-time analysis and capturing the nuances of learning in authentic contexts through building complex models. Another challenge is presenting analysis results to end-users (e.g., students and teachers) effectively to support instructional decision-making (Blackmon & Moore, 2020; Moore, 2019).

LA, or educational data science, is a relatively new, rapidly growing field with significant potential to improve digital learning environments; however, most education researchers, especially those in non-STEM areas, do not have the requisite skill set for applying these tools in their work. STEM jobs are projected to grow 11% between 2020 and 2030 (U.S. Bureau of Labor Statistics) and by 2025, nearly 3.5 million STEM jobs will need to be filled (Lazio & Ford, 2019). Lanahan (2022) estimates nearly 62% of all Americans over 25, 79% of Hispanic adults, and 72% of Black adults do not have an undergraduate degree. An estimated 364,000 new openings in data-driven fields were available in 2020, and data analyst and data scientist positions are some of the toughest to fill (edX, 2020). This indicates a considerable gap in broadening access to leveraging LA as an analysis tool, and the access issue in moving from LA to teaching and learning support would be even more challenging. Thus, policymakers and funding agencies should encourage and support researchers from diverse backgrounds to join the force of shaping the future of AI technologies in education.

Transparency is critical for users to understand the underlying values and the mechanism that make models work and thus evaluate decisions made by computers. With openness in decisions generated from machine learning models, users know how data was collected, selected, and used for training models and may identify potential biases and risks when applying models for prediction in learning contexts. For example, when using an intelligent system to identify students who need help, without the knowledge of how the system works, teachers might be less prepared to give feedback to the student as they are informed about who needs help but not why the student is selected (Holstein et al., 2019). Thus, to some extent, transparency could better leverage human intelligence in decision-making. In such a way, users would be empowered to reason about how intelligence is created, how it is applied, and its potential to perpetuate biases and unfairness. One promising future research direction is investigating strategies for promoting end-users' AI literacy.

## Limitations

A limitation of our systematic review is that we may have missed relevant articles if they were either not indexed by Academic Search Premier or Education Source or did not match the search strings we created. We used broad search terms and then narrowed them down by the quartile ranking of the journals. This filter limits our study because we did not synthesize articles that appeared in lower-ranked journals. We encourage others to replicate our study and include those articles if they can contribute to the narrative about K-12 uses of artificial intelligence.

There is a long history of using intelligent systems to support second language and literacy education. In particular, automatic writing feedback technologies could provide individualized, actionable, and timely feedback to students, including MI Write (Palermo & Wilson, 2020), Criterion (Burstein et al., 2003), Coh-Metrix (McNamara et al., 2010), Writing Pal (Roscoe & McNamara, 2013), and Revision Assistant (West-Smith et al., 2018). However, studies in this area did not appear in our literature search. This is one limitation of this study. Perhaps this is because most such work is not explicitly labeled as artificial intelligence, machine intelligence, or intelligent tutoring system. Instead, they were more commonly described as computer-assisted language learning (CALL) or applied linguistics systems. The omission of this body of research implies that each field might have its own language in describing intelligent systems. When conducting a literature review on Artificial Intelligence, researchers should pay close attention to the language used in different fields. In addition, the field should create spaces for researchers from different fields to share their work, inspiring more collaboration and advances among fields.

## Conclusion

In this systematic review, we synthesized peer-reviewed empirical articles published between 2014 and 2021 that focused on using artificial intelligence in K-12 educational contexts. Our study included articles that used both formal and informal learning environments to introduce a variety of instructional contexts to learners as young as four and into adulthood. We hope our study will spark additional research in this less-studied area of K-12. There is a rich opportunity to identify strategies to introduce technology and digital competencies to students in the primary grades and energize their interests in artificial intelligence, computer science, and technology.

## Disclosure statement

No potential conflict of interest was reported by the authors.

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