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Methodological Analysis of Machine Learning Courses for Elementary to High School Students

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Abstract

The number of studies exploring different aspects of Machine Learning (ML) in K-12 contexts has increased, making it imperative to synthesize existing research. This study presented a comprehensive review of the current state of research on ML education from K-12, drawing attention to both current research hotspots and gaps in the literature that should be addressed by future studies. We looked at 45 articles published at conferences and in journals that focused on certain aspects of K-12 ML education via these four lenses: curriculum development, technical development, pedagogical development, and teacher training/professional development. We found that (a) there is a lack of ML materials for K-8 and informal settings, (b) more research is needed on how ML can be integrated into subject domains other than computing, (c) most studies focus on pedagogical development, (d) there is a lack of teacher professional development programs, and (e) more evidence of the societal and ethical implications of ML should be considered in future research. Although the study's authors note several caveats and suggestions

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for further study, the findings are nonetheless applicable for improving the quality of research in the rapidly expanding field of K-12 ML by educating teachers, researchers, and instructional designers.
Keywords: K–12, systematic review, machine learning, and artificial intelligence.

Introduction

A lot of people are starting to care a lot more about AI these days. Machine learning (ML), a crucial part of AI, is driving a dramatic shift in how we do research and uncover new information (Tellols et al., 2020; Weni Nelmira et al., 2022). Many people in the education sector have taken an interest in the potential advantages of exposing K-12 students to machine learning. Therefore, it is believed that preparing students for life in the ML age via K-12 ML education is important. Understanding the world is made easier when children are exposed to machine learning at a young age since ML is becoming an integral part of people's daily life. Lin et al. (2020) argue that youngsters need to have a knowledge of how machines learn in order to form usable mental models for navigating the increasingly complex world of artificial intelligence and smart technologies. Furthermore, inspiring the future generation of AI researchers and software is a key goal of introducing ML fundamentals.

While there have been recent attempts to introduce the concept of ML to K-12 students, the vast bulk of education on the subject is still found at post-secondary institutions. Hsu et al. (2021) developed AI teaching tools in the form of a simulation game, while Sabuncuoglu (2020) built an AI curriculum for middle schools over the course of a year. In addition, Dwivedi et al. (2021) released Any- Cubes, a prototype toy that children may naturally and pleasantly explore to comprehend machine learning, and (Tellols et al., 2020) produced Zhorai, a conversational agent designed for children to research ML concepts. Curriculum design, pedagogical materials, and technological infrastructure are only few of the many areas where knowledge is expanding in relation to bringing machine learning into K-12 schools (Tellols et al., 2020). As a consequence, the reported initiatives or projects seem to be fragmented, making it impossible to get an overarching perspective of the whole of the current activities and the priority of research in ML education. Unfortunately, AI is inadequately presented in K-12 curricula, and only eleven countries have official AI education programs for students in grades K-12 (Ho & Scadding, 2019). Carter et al. (2020).

Recent efforts to synthesize the relevant research in this field have increased in number. A systematic mapping study (Chora et al., 2021) looks at readily available K-12 education modules that introduce machine learning. While (Chen et al., 2020) examined video games that teach artificial intelligence and machine learning, (Law, & Heintz, 2021) conducted an exploratory evaluation of existing artificial intelligence (AI) learning tools and curriculum to investigate the role of design in fostering AI literacy among students in grades K-12. In contrast to previous research, this article critically examines the published material on ML education from pre-K through 12th grade, including areas like as curriculum, technology, pedagogy, and professional development. All aspects of artificial intelligence and machine learning education and professional development must be comprehended. This includes the technology, curriculum, pedagogies, and chances for teacher training. To help advance this emerging subject, it's important to nail out any potential issues that might arise. Experts speculate that limitations imposed by humans, data, and technology may have contributed to the shortcomings of earlier investigations. The value of this study resides in the fact that it presents a thorough synthesis of studies on the pedagogy of teaching and learning machine learning throughout the K-12 and higher education spectrum. This study is necessary because of the growing number of voices advocating for the inclusion of ML in elementary and secondary education. Interest in this emerging topic may be seen from researchers, practitioners, and educators all across the globe. This has led to a steady growth in the number of initiatives aimed at promoting ML education throughout K-12 settings. Given the increasing number of articles written about the subject, it is crucial to make links among them in order to have a deeper understanding of the origins of the notion and its potential future development. Each study's worth is based on how well it builds upon and contributes to the body of prior research (Lemay et al., 2021). Therefore, it would be useful to compile results from prior research to further our understanding. Considering how recently the topic of machine learning has emerged, further investigation is required to ensure that it is properly incorporated into K-12 education. If we want to know where the field stands in terms of research on how to best teach ML to K-12 kids, we need to look at how successful previous studies were in comparison to the current area of research focus and where there are gaps in the literature. By focusing on these fundamental themes, we can inform the scientific community about the myriad of ML-related teaching and learning resources already accessible.

This study may be useful for educators planning ML materials and incorporating ML technology into their classrooms (Yang et al., 2021). The current research provides a thorough evaluation of the relevant literature, highlighting any gaps as well as suggesting potential new avenues for K-12 ML study. Although research on ML teaching in K-12 is still relatively new, there is enough material out there to do a review and draw conclusions. These are the questions we want to answer with our study:

RO1: The purpose of this section is to categorize the current topics of study in the field of ML education at the elementary and secondary school levels.

RO2: The purpose of this study is to inquire into the challenges associated with ML education in the K-12 setting and to provide avenues for further study in this area.

Background

Teaching through Machines

The influence of machine learning on higher education has not been well studied since the field is still relatively young. It has been taught at various institutions for decades (Chamunyonga et al., 2021). Students studying in computer science or a closely related discipline, such as data science, will make up the vast majority of ML course enrollees (Waring et al., 2020). In today's academic landscape, machine learning is often introduced to students in their second or third year of college, and is covered in a broad range of electives, both within and outside of the field of computer science. Machine learning technology is supporting a shift from analytic problem-solving to a more effective data-driven one by using algorithms that can construct models from training data and predict outcomes from new data (Post et al., 2019). The vast majority of machine learning papers do not address practical issues. When teaching people about machine learning, it's important to make sure they have both the theoretical background and practical experience they need to be successful. As part of the "understanding" component, teachers often introduce students to a particular machine learning approach and show them how to use that method on example data using a particular machine learning software package.

Evaluations of Machine Learning in Schools

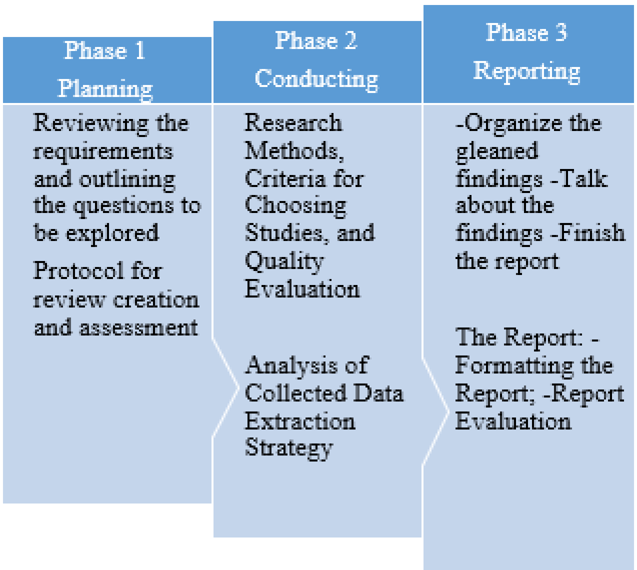
Seven literature papers on K-12 AI/ML education have been located, but no systematic reviews that clearly examine the current priority area of K-12 ML (as it applies to curriculum, technology, pedagogy, and professional development) and recommend issues for future research have been found. These evaluations include ML-related issues including AI literacy, educational games, and games themselves. (Choraï et al., 2021) used 35 studies (2012–2020) to conduct a systematic mapping study (SMS) of K-12 ML teaching modules. 32 IUs focused on ML and neural network principles were found. Due to the complexity of machine learning (ML) concepts, many courses only cover the most fundamental ML activities, such as data management and model learning/testing. The article gathers IU qualities for ML education in content, context, and analysis of how they were produced and appraised from grades K-12. Many IUs offer abstract ML subjects as additional units, from an hour-long introductory workshop to a semester-long course, according to the authors. According to the assessment, many of the publications are not scientific (Chora et al., 2021), and the IUs and their production and review procedures are not harmonized. Games were examined in the second assessment by Chen et al. (2020). A upcoming review paper on K-12 ML games (Chen et al., 2020) offered an overview of key research publications in this field and showed how varied games provide a unique opportunity to teach a variety of AI and ML concepts and topics. The whole research provided a path for stakeholders to find and implement games that meet their needs and offered open RQs in this educational area. After reviewing the study, they discovered 17 games/projects. Current works on AI in K-12 classrooms were examined in the third survey (Law & Heintz, 2021). Law and Heintz (2021) conducted an exploratory study of AI4K12 literature and resources to develop a design framework for K-12 AI-based educational possibilities. They emphasized future possibilities and K-12 design guidelines to help researchers, designers, and instructors create AI learning experiences for K-12 students. Student engagement, built-in scaffolding, teacher and parent participation, equality, diversity, and inclusion, and AI integration with core curriculum are among the design goals.

The fourth review (Burden et al., 2019) examined K-12 ML pedagogies using a narrative approach. The study proposed using learner-centered pedagogies including participatory learning, design-oriented learning, and active learning to teach ML to K-12 students. This strategy promotes student involvement, according to some. (Aafjes-van Doorn et al., 2021; Mardi Mardi et al., 2022) map and assess K-12 ML teaching resources based on their pedagogical qualities, support for ML model construction, and design and evaluation. They uncover 15 tools for students, most of which are employed in short-term extracurricular activities, and show that they leverage students' ML expertise. We examined ML's theory and practice in K-12 schools in the sixth evaluation. This paper covers the paradigm change required to properly incorporate ML into K-12 computing classes. Ng et al. (2021) examined 28 papers published between 2018 and 2021 to identify how academics define AI literacy, how it is taught, and the ethical issues that emerge. Ng et al. (2021) discovered various definitions, most of which used different literacies to describe skill sets in other domains. This study goes beyond earlier assessments of K-12 ML research to assess the present level of knowledge and aggregate available articles to offer paths for ML in K-12 education.

Methodology

K-12 ML research is gaining popularity, making it important to synthesize it. Studying new topics and trends is necessary to enhance knowledge. Thus, we conducted a thorough literature review on ML education history (Garousi et al., 2019; St. Wardah Hanafie Das et al., 2022). Systematic literature reviews might be done following Fig. 1. This study collected articles from six databases since no one database can find all relevant primary research (Table 1). Six databases with publications on computer science and engineering education were selected. Our publishing database searches yielded CSV results. The ones that couldn't be downloaded were written in manually utilizing copy and paste from databases and Microsoft Word. Excel was used to calculate and organize the data, with duplicates deleted by hand.

Figure 1 Methods of doing a systematic literature review



Procedures for the Evaluation Planning

Establishing the relevance of the review

Following the following steps, it is important to first prepare and double-check the review criteria. Review methodology starts out with a focus on the primary goal of existing works on the topic of introducing machine learning to students in grades K-12.

Table 1 Framework for Searching

Academic Databases	Search Design
Scopus	Title
Web of Science (Wos)	Topic
IEEE explore	Abstract

ACM	Abstract
Science Direct	Alternative search
Springer Link	Title

Details about the RQs

Without limiting ourselves to a set time frame, we included prior research into our work. In order to classify the publications for data extraction and analysis, we established the following research questions:

RQ1: Where do researchers stand on the topic of K-12 machine learning education?

In order to comprehend the current state of study in this developing topic, we assessed the chosen papers in light of the current focal area of literature. The data analysis led to four distinct areas of attention: curriculum improvement, technological improvement, pedagogical improvement, and teacher training and professional development.

RQ2: Where should research on ML education in K-12 go from here, and what problems need to be addressed?

The purpose of this study is to examine the shortcomings of previous efforts to explain ML to elementary and secondary school pupils. It also provides a summary of and recommendations for addressing the gaps identified in the literature, which might inform future studies and directions.

Designing the Review Protocol

This review used an approach based on the review procedure. Determining ahead of time what approaches will be used in the review may cut down on inadvertent mistakes. For this review, we used both informal and formal searches to identify research goals and collect data for analysis. The first outcome is offered in the form of related research from the literature review. This helps in formulating research questions that will direct the next literature evaluation.

The Review Is Being Conducted

In this part, we will explain the process that is being used to carry out the review. Methods for finding relevant studies, evaluating their quality, selecting relevant data, and analyzing that data are all part of this.

Methods for Finding

The study's search technique was based on the goals of the investigation. To reduce the number of unrelated publications, we identified keywords, built search strings, designed the search architecture, and executed the search. The research goals of the study informed the creation of the search strings used in the study.

Search keywords

This list of search terms was developed to facilitate the collection of literature on machine learning in the K-12 setting. We compiled current keyword-search methods from studies of the literature on teaching ML to students in grades K-12 (Chora et al., 2021), games for AI and ML education (Chen et al., 2020), and general AI literacy abilities (Law, & Heintz, 2021; Pakorn Akkakanjanasupar et al., 2022). Due to the length limitations of certain databases, it was not feasible to utilize the same and identical terms across all digital publishing platforms. The search architecture is shown in Table 1, and the protocol used for each database is displayed in Table 2.

Table 1 displays the academic databases and search architecture used to locate relevant articles. Title, abstract, and keyword are all part of a title and subject search in Scopus and WoS. Both IEEE explore and ACM were searched for the abstract. For Science Direct, we used the "find articles with these phrases" option in the "advanced search" area, and for springer Link, we looked for the headline. Since the "ALL" option usually produces a large number of unrelated articles, we limited our search to Title/Abstract and Keywords instead.

Each database's search architecture was recorded in its own row in Table 2, along with the protocol used throughout those searches. Table 2 demonstrates the use of Boolean operators "OR" and "AND" to join search phrases in square brackets, allowing for the inclusion of synonyms and alternative spellings. Inclusion and exclusion criteria, which are mentioned below, were used to narrow the search results. Articles and proceedings from conferences written in English were chosen for the reduction. We selected the electronic resources in Table 1 because they represent authoritative, peer-reviewed publications from throughout the world's scientific community (Zhang & Lu, 2021; A Akmam et al., 2022). Moreover, Scopus and Web of Science databases provide powerful search capabilities and cover a wide range of papers (Zhang & Lu, 2021). Papers were hand-searched for other papers by looking through their reference lists. The authors also used a snowball technique to find 12 more publications that they believed to be main research of interest.

Table 2 The database-specific protocol that is actually used

Databases	Protocol
Scopus	TITLE-ABS-KEY ("machine learning" AND k-12) OR TITLE-ABS-KEY ("artificial Intelligence" AND k-12) OR TITLE-ABS-KEY ("machine learning" AND teaching AND k-12))
Web of Science	TOPIC: ("Machine learning" AND K-12) OR TOPIC: ("artificial Intelligence" AND K-12) OR TOPIC: ("machine learning" AND teaching AND K-12)

IEEE explore	("Abstract":"machine learning" AND "Abstract": k-12 AND "Abstract": schools AND "Abstract": kids) OR ("Abstract":"artificial intelligence" AND "Abstract":k-12) OR ("Abstract":"AI" AND "Abstract":k-12) OR ("Abstract":"artificial intelligence" AND "Abstract":teaching AND "Abstract":k-12) OR ("Abstract":"machine learning" AND "Abstract":teaching AND "Abstract":k-12)
ACM	[[Abstract: "machine learning"] AND [Abstract: k-12] AND [Abstract: schools] AND [Abstract: kids]] OR [[Abstract: "artificial intelligence"] AND [Abstract: k-12]] OR [[Abstract: "ai"] AND [Abstract: k-12]] OR [[Abstract: "machine learning"] AND [Abstract: teaching] AND [Abstract: k-12]] OR [[Abstract: "artificial intelligence"] AND [Abstract: teaching] AND [Abstract: k-12]]
Science Direct	((“machine learning" AND "teaching" AND "k-12") AND ("artificial intelligence" AND "teaching" AND "k-12"))
Springer Link	**“machine learning" AND "teaching" AND "k-12" OR "artificial intelligence" AND "teaching" AND "k-12"**

Article selection measures

Table 2 contains the search terms that were used to verify their applicability and ensure they yielded results for all the study's questions. After reading the whole article, we checked it against our inclusion and exclusion criteria to make sure it was appropriate for our study (Table 3).

Methods of selection:

- The use of the English language is required for all papers.
- Presentations and articles published in academic journals and conferences

Journal Article Reporting K-12 Artificial Intelligence and Machine Learning Education Restrictions:

- Scholarly journals, newspapers, periodicals, memos, and patents
- Duplicate papers
- Books and articles focused on the use of machine learning for forecasting
- Articles that didn't focus on how to get kids excited about studying AI/ML in school

Articles were either included or omitted depending on whether or not they met the inclusion or exclusion criteria, respectively. Overall, 45 papers that fit the study's requirements were evaluated.

Quality of research evaluation criterion

To determine the quality of the articles chosen based on the inclusion/exclusion criteria, we used the quality evaluation criteria as our foundation. As with other aspects of this study, the quality evaluation checklist was borrowed from prior research (Lemay et al., 2021; Sonya Nelson et al., 2022). Table 4 displays a checklist outlining the quality of the evaluated literature using a three-dimensional Likert scale with contrasting images for each item.

Table 3 Articles found at each of the three selection levels

Database	**Search result**	**Analyze articles**	**Possible relevant articles**	**Relevant articles**
IEEE	14	14	8	8
ACM	187	187	27	11
Science Direct	68	68	14	3
Springer	25	25	11	4
Scopus	21	21	15	13
Web of Science	43	43	18	6
Snowballing			13	5
Total				45 (w/out duplicates)

Table 4 Checklist for Evaluating Quality

Item	**Assessment Criteria**	**Description of checklist**
1	Is the purpose of the study made clear in the article?	Incorrect; the intended result is not stated. One reason is because the purpose is not entirely made apparent. The purpose is defined and unambiguous, thus yes.
2	Does the article make it easy to understand how to teach or learn AI/ML basics?	True, the lessons on AI and ML are not laid out clearly. The techniques of instruction are only partially revealed, and more research is required. It does, indeed
3	Do the research provide detailed explanations of their findings?	That's not quite right; the story doesn't go into exhaustive detail. The references are necessary to identify the specifics, although it's mostly accurate. It is possible to utilize the methods or tactics using the specifics given.

4	Is there a methodology presented in the studies?	False, there is no description of methods presented. The approach is there, kind of, but it's not really obvious. In a word, yes.
5	Do scholarly works based on the study get cited by other scholars?	While not entirely unique, this work has been referenced by just 1-5 other publications. This work has been cited in more than 5 publications.

Conclusions from the quality analysis

The studies included in this analysis were rated according to their quality using Table 4. In response to question 1, all 45 publications clearly stated their research goals, however only 19 articulated their educational goals. In the second quality assurance (QA) section, we looked at how well the studies explain how AI and ML are taught from the ground up. Thirty-five papers offered detailed information on the creation, deployment, and assessment of tools and exercises meant to introduce students to AI and ML. Eight of the articles, however, provided an overview of the established AI teaching syllabus, curriculum, and standards, and investigated the elements that affect students' motivation to study AI. With regards to QA3, we found 8 publications that described a researcher-designed curriculum with detailed details that other researchers might use. In depth descriptions of 15 ML education resources were provided. In addition, 16 publications completely detailed methods used in previous research to teach ML, but specifics of teacher training activities were published in just 4. Fourthly, the publications should clearly demonstrate the methods used. In 28 publications, the methods and procedures used in the study were clearly outlined (e.g., experimental, design-based, or mixed-method). Only five of the publications indicated the methods used, and none of them provided any real detail. In addition, 10 of the papers focus almost exclusively on the strategy they adopted, rather than on the research methods used by the studies themselves. The number of times this research was referenced in other publications is the last criteria. The citation counts of the publications were analyzed using the Google Scholar database (August 2020). There were 45 publications examined; 15 were cited more than five times by other papers, 18 were cited between one and five times, and eight had no citations at the time of the check. One item was completely absent from the database. Since the academic database will automatically update the citations when the works are referenced, the answer to QA5 might change in the future.

The information was culled from the supporting documents in accordance with the research by (Garousi et al., 2019). After carefully reviewing the gathered data, an Excel spreadsheet was created and finished. We've underlined the section headers you need to use to access the data:

- Research Aims
- To have access to goods, equipment, and other resources
- Objectives for Instruction
- Methods of Instruction and Coursework
- Topics explored in the research
- How many scholarly works cite the investigation

This research makes use of inductive analysis since its ideas come straight from the facts. Knowledge abstraction is achieved using this method by first codifying and then creating categories to help define the topic being studied. The aforementioned list titles are subsumed under the more general categories of curricular development, technological development, pedagogical development, and teacher training/professional development. All of the found articles were taken into account throughout the data extraction and analysis procedure. If a document is missing crucial information that might be extracted from its table, it is likely that the corresponding cell in the table reads "not available."

Results

Reforming Education's Curricula

Multiple ML education plans have been produced by scholars in various parts of the world. Our research has informed the development of a comprehensive AI education curriculum that includes pre-K through 12th grade (Ayanwale et al., 2022; Eti Hadiati et al., 2022). The seven studies that were discovered all had the same goal of helping kids get a handle on AI. However, two of the studies explicitly indicated that knowledge-based systems, supervised machine learning, and generative AI were the three AI principles that students were required to master. Six out of the nine publications used robots as a tool to help educate AI. Examples include PopBot, a social robot built using a smartphone, LEGO bricks, motors, and sensors. Games, the Alexa app, an online simulator, and unplugged alternatives all fall under this group of tools. In addition, there are games, puzzles, riddles, conversations, group projects, interactive demonstrations (Ayanwale et al., 2022), and robot-building activities that may be used (Vartiainen et al., 2021). A workshop or after-school activity kept the kids busy.

Innovation in Technology

The K-12 education spectrum was taken into account while creating ML teaching resources. The literature identifies the following resources: PRIMARYAI, SmileyCluster, AlpacaML, Zho- rai, LearningML, and VotestratesML. Online platforms are the most common sort of tool aimed at helping kids learn about machine learning. Researchers may now offer ML to students through a variety of disciplines and topics. Researchers and producers of the resource say that teaching kids how computers represent information is one of their main goals. Smiley Cluster was used to introduce kids about k-means clustering. Embodied models of gesture (e.g., Zimmermann- Niefield et al., 2020) and the use of mind mapping and visualization were among the many teaching and learning activities used to introduce the tools to students. Students may also engage in scientific inquiry behaviors like question asking and explanation via the use of modeling and simulation games.

Growth in pedagogy

From the available literature, we may infer that ML instruction has taken place at the elementary, middle, and high school levels. These have also been conducted in a wide range of non-academic environments, including but not limited to homes, summer camps, workshops, and laboratories. One publication (Kucuk & Sisman, 2020) is focused with attracting more women to the field of artificial intelligence, while the other research we found aim to figure out how to teach fundamental machine learning ideas. Multiple resources were used to help students better understand ML, as seen by the articles presented below. Examples of such resources include the Google Teachable Machine (GTM), robots, Scratch, RapidMiner, a bounding box, data cards, a collection of toy cookies, and image cards. Few publications used offline activities to teach students about AI's core concepts. Students were given many ways to get acquainted with the course's objectives. Project-based learning, in which students and teachers work together to develop an ML-based solution, is one of the most popular methods. The majority of the publications included for this summary relied on collaborative projects to introduce students to ML concepts. Students were also exposed to active learning strategies through classroom activities and guided conversations. When kids work together to teach a computer using just their bodies, they are using participatory learning and collaborative approaches, which are borne up by the literature. Finally, the lecture technique was used in addition to other methods to teach AI ideas.

Educators' Capacity Building and Training

Teachers play a crucial part in every educational system, yet we were only able to find a small number of publications on the topic of teacher education. Researchers in ML for K–12 have paid the least attention to this area. Only four papers were located that dealt exclusively with AI and ML education for educators. The program made use of four Google products: Machine Learning for Kids, GTM, Google Quick Draw, and Google's A to Z of AI cards. Since the co-design was conducted digitally, tools like Zoom, Slack, and Miro were used to ensure smooth meetings. The perspectives of educators with and without AI education expertise are compared (Yang et al., 2021). Only one publication jumped up as having a specific emphasis on ML training for educators (Law & Heintz, 2021). SmileyDiscovery was created by (Law, & Heintz, 2021) to facilitate low-barrier ML-empowered Scientific Discovery in the K-12 classroom without requiring instructors to have specialized ML knowledge. On average, sixteen teachers from elementary, middle, and high schools participated in workshops based on the papers that were identified. Methods like gamification and project-based learning are used, along with the more traditional methods of interactive instruction that include real-world applications.

Discussion

This data illuminates the K-12 ML research focus. We organized our findings discussion around four primary topics from the articles we read. Subheadings include curriculum, technology, pedagogy, and teacher training/professional development. This method lets us find and arrange material for each of the four categories. We examine the review's results, their implications, and research suggestions here.

Since ML is so new and promising, K-12 education has started exploring it. We performed a systematic review to assess K-12 ML research, recognize previous findings, and propose topics for further study. Our approach showed that research articles boost secondary ML education. Studies have taught ML to young kids, but the literature indicates minimal disagreement over AI activities for younger children. ML programs for younger pupils should be tested to see whether they work. Thus, stakeholders and educators might use ML materials for K-12 pupils.

More research on ML-focused activities and interventional studies with non-academic students is required. This is crucial because learning is a cumulative process that requires connections and support across all learning experiences, including those at home, school, and in the community. According to studies with young children in homes where ML is used as a teaching tool, embodied engagement with machine learning systems improves learning and computational thinking for novices. One study examined the ML process with children in a household setting, whereas others, including (An et al., 2020), promoted AI literacy in museum-like settings and online. Since there are few K-12 informal ML studies, our review shows that further research is needed to understand how informal-context-based treatments increase ML.

Third, well-prepared instructors are needed to integrate ML principles into K-12 curriculum, but teacher preparation research is scarce. Thus, additional ML research is required to help teachers understand ML. Thus, ML teachers' preparedness may be significant. Knowing teachers' acceptance and tendency for ML in the classroom may indicate their interest in teaching technology and impact their pedagogical choices, therefore understanding these characteristics is vital (Christensen & Knezek,2018). If teachers are given ML advocacy tools, they will participate.

Fourth, incorporate ML curricula to STEM and liberal arts courses. ML may extend pupils' academic and personal interests (Zimmermann-Niefield et al., 2020). Social studies may help students learn and think critically about ML, but ML understanding's role in technical and computational skills must be validated. Including ML in all curriculum, not just STEM, will better prepare students for an AI-dominated future. If you're concerned about teaching AI to kids without access to computers, this may help them get started. ML course assessments may also evaluate ML classroom introduction. This example shows an ML learning grading rubric created by (Aafjes-van Doorn et al., 2021). In countries without standardized testing, formative assessments may be needed to assess students' ML knowledge.

Pedagogical and tool development dominated the selected research. We investigate ways to incorporate machine learning into secondary and elementary education curriculum. A well-considered pedagogy may enhance ML teaching and student learning, therefore instructors must master strategies that assist students understand complicated topics. Some research have focused on K-12 methods to demystify ML, emphasizing the necessity to educate kids about ML. Most education involves group projects, exercises, and lectures. Since the reviewed studies seldom specified the pedagogical approaches and theoretical grounds, it is hard to determine how particular ML tools were really used in teaching. Technology's role in teaching kids new concepts cannot be emphasized. ML education materials may have proliferated. Visual technologies like Google's Teachable Machine and Learning ML teach ML without code. (Gresse von Wangenheim et al., 2022; Pakorn Akkakanjanasupar et al., 2022) confirmed that the tools are free and available online for usage in schools with stable internet connections. K-12 ML curriculum construction, teacher training, and professional development needed more study. Additional grade-level material is needed to teach ML in schools. More regional and age-specific courses should be developed. Only eleven countries have government-endorsed K-12 AI curricula, according to UNESCO study, suggesting more curriculum creation (Carter et al., 2020).

Fundamentally, there is no AI or ML K-12 teacher training program. A curriculum that covers AI and ML will assist pre-service teachers teach these subjects at all school levels. AI education's future depends on teachers' expertise and methods (Yang et al., 2021). According to UNESCO study, AI teachings succeed when instructors are prepared and given resources (Carter et al., 2020; Muthmainnah et al., 2022). There is some literature on pre-service teachers and ML, but more study is required to construct an ML teacher professional program and better understand their views. Professional development programs that include in-service teachers seminars and a collaborative design approach in which teachers and researchers co-create learning materials and activities may enhance ML usage in classrooms.

As ML becomes increasingly prevalent in K-12 classrooms and curricular areas, its social and ethical implications must be stressed. Moral concerns in computer science classrooms boost student interest. One exception: a middle school curriculum on AI and ML ethics. More ML resource research and ethical content design are needed. Thus, even the smallest children may begin to understand the relevance of their daily AI technology. Machine learning proficiency must be assessed in future investigations. Results match (Chora et al., 2021). The duration of the intervention, which may vary from workshops to short courses, and the difficulties of monitoring student progress make this particularly true. Students and instructors might benefit from greater input.

Conclusion

This literature review on K-12 ML education suggests future research and ways to define and cultivate ML knowledge. Our study demonstrates that ML tools were designed for all-level classes. High schools have the most supplies. It is also taught in classrooms rather than informally. Since most studies are on computer skills, ML needs more research into core subjects and domains. Three-and-a-half percent of study evaluated ML tools, whereas 37% addressed pedagogical enhancement. Eighteen percent of the papers focus on curriculum development, while nine percent on teacher training and professional development. Project-based learning, which involves students co-creating ML-based solutions, and active-based learning are popular educational methods. In K-12 schools, visual tools like Google Teachable Machine, Learning-ML, and PIC make ML more accessible to students.

K-12 ML research is promising. This research compiles earlier ML studies on K-12 education. Our findings suggest additional research is required in this area. When developing ML projects or investigations for K-12 students, academics and AI/ML experts should consider the following: We need to (a) develop more ML activities for K–8 education, (b) incorporate ML ideas in subject domains other than computing to promote ML integration in schools, (c) create assessment for ML that can be relevant across levels to allow students to compare their ML understanding across learning settings, and (d) consider the societal and ethical implications of ML to better understand students' potential real-world application of ML.

Finally, because ML is now part of K-12 curriculum, a library of activities, platforms, and evaluations for stakeholders would benefit the discipline. This might help educate instructors or explore the activities or tools in a new location with fresh samples. ML may be integrated into other subjects from kindergarten through high school, with pros and cons. Promoting ML education via professional-stakeholder relationships. This would strengthen and spread ML education and inspire students to use their new skills.

Recommendations

First, as most of the included research only employed small samples to evaluate the system, a larger study is required to establish the usefulness of the used approaches and generalize findings to broader settings. Despite a range of assessment methodologies (Chen et al., 2020), empirical evaluation of studies and projects remains crucial, and a rigorous rubric should be devised to evaluate participants' learning gains. Consider longitudinal pedagogical research while teaching computational thinking and machine learning. Supervised ML, especially classification tasks, is the most researched kind of ML. We need further study to see whether youngsters can understand advanced ML procedures.

Many studies note a lack of learning resources, recommending that future research should concentrate on producing integrated and AI materials for students, novices, pre-service, and in-service teachers. Research also examines educational design and topic expertise to improve AI identification and interest (Yang et al., 2021). Studies also found a lack of teacher training, highlighting the need for greater research to help educators create learning materials and integrate AI technology into the classroom (Yang et al., 2021). This study may give future instructors with valuable knowledge. Teachers' understandings and experiences co-designing and scaffolding AI in classrooms from diverse cultures may provide more useful information (Yang et al., 2021). To spread AI knowledge, Co-design workshops are recommended for kindergarten through high school teachers to assist students construct machine learning applications. This helps kids understand machine learning, data sets, under/over fitting, testing, and system upgrades. Future initiatives may also improve parental co-design engagement (An et al., 2020; Abdul-Hussain et al., 2022). Long research experiments are also advised. It may provide fresh ideas rather than merely describing the notion, making it useful. Many platforms and technologies are designed to teach young children about machine learning. GTM, ML4Kids, scratch, Popbots, and Anycubes are examples. How they're utilized, how learners' preferences alter between platforms, and how authentic the information is must be evaluated. Thus, future study should examine these tools' pros and cons. This information may help choose learning tools and resources for future learning activities or platform specifications.

Limitations

As is typical with review articles, this one includes a few caveats. To begin with, the scope of this study is rather narrow since just six databases were consulted. In addition, five search phrases were used, including variations of the words "teaching," "machine learning," "artificial intelligence," and "K-12" or "school." The phrases used in the searches are typical of practically all reviews in the field. Use of closely similar search phrases, such as "data science" OR "deep learning," may get better results. Our search methodology may also affect how we show results and hint at the scope of our generalizations. K-12 AI researchers (Kucuk & Sisman, 2020) have also pointed out a lack of female participation in AI-related fields. However, we were unable to include this region in our analysis because so few participants provided demographic data. One restriction is making use of only English-language sources, such as journals and conferences. In this case, 45 papers were located using specific search techniques across 6 databases and served as the basis for this study. Strategy and online bibliographic databases may have led to increased publications, nevertheless. In light of this, the findings of this study should be seen as an investigation of ML education rather than a comprehensive survey of the topic. We anticipate that this study will provide helpful insights for computer science and engineering educators.

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