(Authors' Draft)

Introducing Artificial Intelligence Literacy in Schools: A Review of Competence Areas, Pedagogical Approaches, Contexts and Formats

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Abstract. Introducing artificial intelligence (AI) literacy to school students is challenging. As AI education is constantly growing, educators can struggle to decide *which* content is relevant and *how* it can be taught. Therefore, examining which practices and formats have already been evaluated with students and are used repeatedly and which are challenging or should be explored further is necessary to facilitate teaching AI and encourage the development of new activities. In this literature review, we address this need. Using a directed and conventional content analysis, we systematically analyzed 31 cases of introducing AI literacy in schools in terms of three categories: (a) competence areas, (b) pedagogical approaches, and (c) contexts and formats. When analyzing the results, we identified underrepresented competence areas and summarized common pedagogical practices and recurrent formats and contexts. Additionally, we investigated the approach to using data to make abstract AI knowledge accessible to novices.

Keywords: Artificial intelligence literacy, AI education, data literacy.

1 Introduction

Integrating artificial intelligence (AI) literacy into schools has been on the educational research agenda for several years. As students interact with AI technologies every day, they should be empowered to critically evaluate these technologies [1, 2], use them as a tool for effective human–machine collaboration [3], and be aware of how insights are gained from data at an early age [4]. Consequently, initiatives to foster AI literacy are emerging worldwide, and the number of educational materials and tools is increasing.

Several studies have been published in recent years to provide educators with a solid foundation for AI education. Most of these secondary studies in the field have focused on conceptualizing AI literacy [2, 5, 6] or examined specific topics in AI education, such as machine learning [7–9]. However, in addition to answering the question of *which* content is essential in AI education, there is also a clear need to explore *how* AI should be introduced to students.

In this study, we address this need by conducting an exploratory review of 31 AI case studies that were empirically evaluated with students in schools. Each study is systematically analyzed in terms of three categories: (a) competence areas, (b) pedagogical approaches, and (c) contexts and formats. The main contributions of this paper are the following: (a) analysis of common pedagogical practices, particularly the use of data to make AI knowledge accessible to novices; (2) identification of underrepresented competence areas in AI education; and (3) investigation of recurrent formats and contexts in this field. From a historical perspective, these contributions provide an overview of the current AI education landscape in schools, which can be used for comparisons in the future.

The paper is organized as follows: In Section 2, we provide background on AI literacy in school education and discuss related works. In Section 3, we describe the methods used for this exploratory review. In Section 4, we outline the analysis results; the presentation of results is organized into the three categories that served as the basis for the analysis. We discuss the findings in Section 5 and, finally, offer suggestions for future research in Section 6.

2 Artificial Intelligence Literacy in School Education

According to Long and Magerko [2], *AI literacy* is a set of competencies that enable individuals to evaluate AI technologies critically; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace. Although some suggestions confine AI education to machine-learning education [7, 9], researchers also use the term "AI education" to describe approaches that focus on introducing AI to school students [10, 11].

Several guidelines have been published on AI literacy in schools. Long and Magerko [2] provided a conceptual framework, including a detailed set of AI literacy competencies for learners and design considerations of learner-centered AI for developers. Tedre et al. [4] proposed a concept of computational thinking 2.0, which extends basic computational thinking by adding the mental skills and practices students need for training machines. Touretzky et al. [1] suggested five major ideas of AI that should be introduced to every student in their education: perception, representation and reasoning, learning, natural interaction, and societal impact. Researchers have often referred to this framework when developing local guidelines for AI instruction in schools (e.g., [12]). Zhou et al. [5] provided guidelines for designing AI learning experiences for K–12 students based on prior research and presented a list of future opportunities to strengthen the effectiveness of AI curricula.

In addition to conducting intense conceptual work on AI literacy guidelines, researchers have empirically evaluated several approaches with school students. For example, Sintov et al. [13] and Williams et al. [14] investigated the use of robots and game-based learning to introduce AI to school students and found the approaches successful. Srikant and Aggarwal [15] suggested that collecting and analyzing students' data would enhance students' learning of AI.

Nevertheless, little emphasis has been put on systematically inspecting practices and pedagogical approaches for introducing students to AI at the school level. However, before new materials and tools are developed, researchers and educators should ideally know which approaches and formats have already been evaluated with students and are effectively and frequently used and which are challenging or should be investigated in more detail in the future. Moreover, knowing which competence areas educators are focusing on in practice and which areas are underrepresented in the current AI education would also be valuable to determine whether all pertinent dimensions are being covered or whether adjustments will need to be made in the future when new approaches are developed.

Consequently, in our exploratory literature review, we focused on the following two research questions:

- **RQ1:** Which competence areas are underrepresented in the current AI literacy approaches?
- **RQ2:** What are the common pedagogical practices, recurrent formats and contexts in AI education?

3 Method

To answer the research questions, we conducted an exploratory literature review using qualitative research methods. In this section, we describe the selection of studies for the review and analysis process in detail.

3.1 Selection Process

To find relevant literature, we used the snowballing and keyword search approaches. Snowballing refers to using the reference list of a paper or the citations to the paper to identify additional relevant papers [16]. While snowballing, we studied the bibliographies of the works cited on AI education provided by Long and Magerko [2], who analyzed 150 documents on AI literacy, and by Zhou et al. [5], who reviewed 49 more recent works on AI education. We included the studies whose titles indicated practical implementation of AI topics with students in the start set for further analysis. The search helped us find relevant keywords for the second stage of the search.

Afterward, to include more recent studies, we used the following search string on Association for Computing Machinery (ACM) Digital Library: [All: “ai education”] OR [All: “ai literacy”] OR [All: “machine learning education”] OR [All: “artificial intelligence literacy”] OR [All: “artificial intelligence education”] AND [Publication Date: (01/01/2020 TO 01/31/2022)]. We chose this database since ACM is the world’s largest educational and scientific computing society [17] and because its digital library provides access to a vast number of contributions to the computer science field [18]. Additionally, we searched Google Scholar for the same terms and evaluated the first 50 search results.

We selected relevant papers based on the following inclusion and exclusion criteria: The selected study (a) is grounded in research, (b) the primary objective is the introduction of AI literacy in school education, (c) is evaluated with students, (d) is published in English, and (e) is accessible. Using these criteria, we first filtered out studies by reviewing their abstracts and keywords. Of the remaining studies, additional studies were excluded after reading the full texts, resulting in 31 studies published between 2010 and 2021. The complete list of all studies selected for the literature review can be provided upon request.

3.2 Analysis Process

For analyzing the selected studies, we used a combination of directed and conventional qualitative content analysis methods [19]. The directed analysis methods rely on existing theories or prior research that can be used for coding the text passages and include the definition of codes prior to the analysis. If no code is suitable, a new code can be created during the analysis. Conventional content analysis is an inductive method and does not require prior theory. The codes are defined as part of the analysis. Section 4 explains in detail how we determined the codes.

In the first step, one researcher (data extractor [20]) defined the codes, read the studies, and coded the relevant passages using predefined codes. The relevant text segments were then extracted into a table. In the second step, another researcher (data checker) reviewed the coding for six random papers to validate the first researcher's coding. The data checker either confirmed that the coding was correct or discussed the issues with the data extractor to reach an agreement. Initially, the data checker agreed on 89.17% of the coded text passages. After discussion, the data extractor and data checker reached 97.5% agreement. In the end, for the codes defined for the directed analysis method, we calculated the frequency of their occurrence with respect to the totality of studies. The complete results of coding can be provided upon request.

4 Results

We conducted an exploratory literature analysis according to the three categories: (1) competence areas, (2) pedagogical approaches, and (3) contexts and formats. In the following three subsections, we present the results. Each subsection is similarly organized. First, we explain how we coded and analyzed the text passages. We have chosen to explain the definition of the codes in this section rather than in Section 3 for ease of reading. Second, we summarize the results of the analysis for each category.

4.1 Category 1: Competence Areas

To analyze the underrepresented competence areas and answer RQ1, we used the Dagstuhl triangle, a framework for describing the phenomenon of digitization that should be included in education [21]. This approach involved examining each study from three perspectives: (a) technological ("Does the study foster technological competencies? Did the students learn how AI works?"), (b) socio-cultural ("Does the study promote socio-cultural competencies? Did students learn what the impact of technology is?"), and (c) user-oriented ("Does the study promote a user-oriented perspective? Did the student learn how to use AI?").

From the technological perspective, most of the analyzed approaches aimed to enable students to understand the technical background of AI. This trend can be observed in all age groups. For instance, Vartiainen et al. [25] argued that young children (<= 6 years) should be able to explain how a computer learns to classify emotions and illustrate how this goal might be achieved. For middle school students, DiPaola et al. [22] claimed that the students should be able to articulate how recommendation systems function. For high school students, the requirements are more specific and extensive. Vachovsky et al. [23] developed a summer school concept that provides participants with an overview of the technical methods used in humanitarian applications.

The socio-cultural perspective was addressed by just over half of literature. Approaches ranged across the spectrum, from assessing the societal impact of AI technologies [22] to examining algorithmic bias [26] and from describing the limitations of AI in real-world settings [27] to considering issues of data privacy [28].

The third perspective, user-oriented, was also considered in most approaches. The analysis indicates that students are expected to use technology to accomplish the assigned task, such as training the device to recognize gestures [29] and deploying machine learning models using given software [12, 30]. Only a few works reported that the students learn how to meaningfully use AI in their everyday lives and solve problems relevant to their everyday lives [29, 31].

In short, we found that the analyzed literature covers all three perspectives of the Dagstuhl triangle to varying degrees. However, a small number of the studies covered all three perspectives simultaneously. The technological and user-oriented perspectives were evidently dominant, meaning that most studies concerned students' ability to know how AI systems work and how to use them but not what their effects are.

4.2 Category 2: Pedagogical Approaches

We based the analysis of the pedagogical approaches on Sheard and Falkner's [32] classification of the key pedagogical practices used in computing education for answering the first part of the RQ2. Each approach we identified was allocated to one or multiple practices from the following list: (a) active learning (a range of practices in which students are involved in actively doing and reflecting on their learning), (b) collaborative learning (a range of practices wherein students collaborate in the learning process), (c) contributing student pedagogy (a range of collaborative practices in which students produce valued artifacts to contribute to other students' learning), (d) blended learning (a range of active instructional practices that blend modes of learning, typically online and face to face), and (e) massive open online course or MOOC (pedagogic approaches built on top of the MOOC format). If the analyzed approach did not fit into any of our criteria or explicitly built upon other approaches, we included it in the category "Other approaches."

Furthermore, from a pedagogical perspective, research suggests that using concrete data instead of abstract concepts may be beneficial for educating school students on AI [5]. Srikant and Aggarwal [15] proposed that being involved in collecting and entering data could provide students with greater ownership of the exercise and enhance the activity element. Register and Ko [33] showed that one way to develop self-advocacy skills in the domain of machine learning is to teach the learner with their personal data. Consequently, we decided to explore how data is used in current pedagogical approaches to introducing AI in schools. For the analysis, we used the data lifecycle provided by Grillenberger and Romeike [34] as a structuring framework because the data lifecycle is widely used to describe content and competencies relevant in the context of data and data literacy [35]. For every stage of the data lifecycle (acquisition, cleansing, modeling, implementation, optimization, processing/analysis, visualization, evaluation, sharing, erasing, archiving), we answered the question: "Is this stage covered by the respective approach, and if so, how is it embedded?"

The analysis of pedagogical approaches indicates that active learning was a key factor in learning AI in all the studies considered. For instance, students taught conversational agents and evaluated how well the agents learned [36], or they redesigned YouTube to understand how it uses stakeholders' needs and users' data to deliver content [22]. Collaboration was also evident in the analyzed studies, although to a lesser extent than active learning. Several researchers have described students working in pairs or groups [23]. However, some researchers found it challenging to implement collaborative learning due to COVID-19 [11]. Overall, we found that pedagogical approaches were characterized as "low floor" [29], "hands-on" [37], "playful" [38], and "project-based" [29]. No use of blended learning or MOOCs was reported.

After analyzing the literature for how the data was used in each of the studies, we found that most works involved using data for introducing machine learning concepts. Two studies reported the use of data in the context of knowledge-based systems [14, 37]. The most common stages of the data lifecycle to which the activities referred are the analysis and evaluation stages. Occasionally, the acquisition, modeling, and implementation stages were addressed. Students were reported to collect the data using scientific tools and methods and build machine learning models by experimenting with different features and adjusting model parameters to predict a better outcome [30]. Even young children were reported to be able to use subjectively meaningful data, such as their bodily expressions, to train the machine learning models and to reason about when the model breaks and why [25]. However, information about the specific content is sometimes lacking, e.g., what techniques the students used for "basic data processing" [39] while preparing the data. Although cleansing, optimization, and especially visualization are common practices in AI when conducting explorative data analysis or evaluating model performance [40], studies rarely address them.

In summary, we found that active learning and collaborative learning were common approaches, whereas blended learning and MOOCs were not reported to be used. Most studies involved one or more phases of the data lifecycle, suggesting that educators often used data literacy in AI educational contexts.

4.3 Category 3: Contexts and Formats

To investigate the pedagogical context and answer the second part of RQ2, we used the structure proposed by Charlton and Poslad [41]. For coding, we also used the method of conventional content analysis method. Each study was investigated for (a) student context and purpose setting (for each study, the following questions were answered:

“How is the study embedded in students’ everyday lives? Can young people get creative with AI and solve problems they care about?”) and (b) the formal context in which the reported intervention took place (“Did the reported intervention occur during computer science school lessons, in context of other subjects, or outside the regular school lessons?). While evaluating formats and contexts, we also collected statistics on the duration, target group, sample size, participants’ background knowledge, and teacher involvement.

The findings indicate that the activities described in the studies were aligned with the students’ context though they had an artificially created purpose. While the studies referenced contexts from students’ everyday life (such as games [31], friends [15], animals [12], food [42]), students performed artificially created tasks (e.g., using particular software to train a classification model with a dataset that is prepared by the educator [43]) and did not transfer their knowledge into other domains. Students applying knowledge to new contexts and working on projects they cared about were rarely reported (e.g., [44]).

The formats used in the analyzed studies ranged from short activities and one-day workshops to summer schools lasting several weeks. Most activities reported were not part of the regular computer science curriculum and occurred in the context of other subjects (e.g., social sciences [39]) or outside regular school classes. The activities were based on the assumption that students had no prior knowledge of AI and were conducted by researchers, though the studies did not specify whether school teachers were also involved in the education process. Only Heinze et al. [45], Burgsteiner et al. [37], Williams and Breazeal [46], Kaspersen et al. [39] reported involving teachers and preparing them to be multipliers and test AI materials.

In summary, we found that the topic of AI was embedded in various subjects but rarely in computer science classes. Students were more reported to learn about AI in restrictive, artificially created contexts than in projects that interested them and in which they could transfer their knowledge to other domains.

5 Discussion

We conducted an exploratory review of 31 studies that focused on introducing AI literacy in schools. We analyzed each study in terms of the three categories and presented our results in Section 4. In this section, we discuss the key findings.

1. Most studies were concerned with developing students’ ability to know how AI systems work and how to operate them but not what their effects are.

While analyzing the competence areas, we observed that the socio-cultural perspective was clearly underrepresented, a concerning finding in light of the need to develop responsible practitioners and critical users of AI, as is stressed by organizations such as United Nations Educational, Scientific and Cultural Organization (UNESCO) [3]. This result is consistent with the findings of Zhou et al. [5], who noted that ethics are underrepresented in existing approaches to AI education. In contrast, the technological perspective was addressed in most studies. Interestingly, however, most of the studies were not anchored in the context of computer science education.

2. Students were actively engaged in the learning process. However, they were frequently reported to learn about AI in restrictive contexts. Moreover, they did not apply their knowledge to new domains.

Analysis of the pedagogical practices showed that active learning was among the most common approaches, as well as collaborative practices. However, while investigating the context and purpose settings, we found that activities for introducing AI mostly addressed artificially created, pre-structured tasks and that students were not expected to develop their knowledge and apply it to new contexts and domains. Such an approach is characterized by Bers [47] as a playpen environment in contrast to the playground, where the students have more room to move, explore, experiment, collaborate, and apply the knowledge to new contexts. Since the goal of modern education is to empower students to think creatively, playpen environments should be a stepping stone, not the destination [48].

3. AI education is still a marginal topic in schools. However, if the goal is to spread AI literacy widely, it should be integrated into regular school lessons. More formats should be available for advanced students, and teachers should be more involved.

In terms of formats, the studies typically targeted students outside regular school hours, indicating that AI is still a marginal topic in school education. Approaches for more advanced students were rarely reported, which is expected and in line with the finding of [7], who emphasized that most instructional units address beginners. Moreover, there was little reported involvement of teachers. Consequently, at first glance, it appears that most studies were conducted by researchers. This trend is consistent with the statements of Marques [7, 49], who noted that there is little work involving K–12 teachers. One reason, as stated by Vazhayil et al. [50], could be that teachers have little belief in the potential of AI education. However, to sustain AI education in schools, teachers need to be involved and trained.

4. AI education appears to be inextricably linked to data literacy. However, a solid theoretical foundation that explores the relationship between AI and data literacy is lacking.

In exploring the approach of using data in AI education, we found that data is used in the context of introducing machine learning and knowledge-based systems. Each study involved one or more phases of the data lifecycle, though there was a lack of details about the specific contents, e.g., which techniques the students used to optimize the model. This tendency indicates an inextricable link between AI education and data literacy—the ability to collect, manage, evaluate, and apply data critically [35], as already suggested by Long and Magerko [2], Zhou et al. [5], Tedre et al. [4]. However, a solid theoretical foundation that explores the relationship between AI literacy and data literacy (including related concepts such as critical big data literacy [51], and statistical literacy [52]) is lacking. Future research should explore the theoretical underpinnings of these concepts to clarify how AI education can be enhanced through data literacy.

6 Conclusions

This paper analyzed existing approaches reported in the literature to teach AI literacy to school students. After identifying underrepresented competence areas, we examined common tendencies regarding pedagogical practices and the formats and contexts in AI education. Subsequently, we investigated the approach of using data in AI education.

The findings indicate that the socio-cultural perspective is underrepresented in current practical studies. This finding is concerning if the goal is to achieve responsible practitioners and mature, critical users of AI who are aware of the general conditions surrounding AI. Consequently, future research could suggest ways to integrate more approaches from the field of ethics into AI education. Another tendency that we discovered is that students are often supposed to learn about AI in restrictive, predefined contexts rather than in subjectively meaningful projects they care about. However, since the goal of modern education is to empower students to think creatively, future research should investigate how educators can transfer from pre-defined, step-by-step instructions to more open-ended projects. Lastly, the analysis indicates that educators use data in various contexts of AI education, suggesting that AI literacy is inextricably linked to data literacy. Therefore, future research may investigate whether personally meaningful data may be used as a tool to promote AI playgrounds in the school context.

Although this exploratory study provides comprehensive insights into the research field and trends in AI education, it is not exhaustive as AI education is a dynamic field that is consistently evolving. Therefore, we recommend that future researchers conduct a systematic literature review to obtain a holistic picture of the research field. We also encourage to them to explore the relationship between AI and data literacy to support future practical concepts for AI education through the solid theoretical foundation.

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