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How to Playfully Teach AI to Young Learners: a Systematic Literature Review

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ABSTRACT

Children are experiencing Artificial Intelligence (AI) devices in their daily lives. It is crucial to provide them with knowledge concerning how AI works, for enabling them to use AI responsibly and participate actively in their AI-driven future. To support motivation and engagement, playful tools are often used in technology education for K-12 children. This paper offers a systematic literature review of tools for teaching AI to K-12 learners in a playful manner. The most relevant articles are classified and analysed in terms of the nature of the tools they use, that is, whether tools are digital, partly physical and partly digital, or unplugged. Their analysis also considers the target age, the educational focus, and whether their impact is evaluated. According to the results of the review, there are tools for learners of all school grades, and digital tools are the most investigated. Moreover, several studies with tools tend to evaluate engagement and learning but in different manners. The paper concludes by discussing the evaluation aspect, general future work directions and limitations in relation to HCI and education for children.

CCS CONCEPTS

• **Human-centered computing → Human computer interaction (HCI)**.

KEYWORDS

Artificial Intelligence, play, game, gamification, learning, K-12 education

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1 INTRODUCTION: BACKGROUND AND MOTIVATION

1.1 Background

Artificial Intelligence (AI) is a field which was born when computer science was, and which has been evolving along the years in different directions. One of the main academic references for AI is the textbook by Russell and Norvig [35]. This adopts a rather operational definition of what AI is, by considering what AI agents are: "We define AI as the study of agents that receive percepts from the environment and perform actions". AI approaches differentiate according to how to move from percepts to actions, e.g., through search, planning, knowledge representation and reasoning, besides machine learning (ML).

Nowadays, children have access to AI-enabled tools, such as smart toys and AI assistants, from an early age, but studies have shown that children lack a clear understanding of how they work and of possible risks related to interactions with them [25]. Even if the interest in teaching AI to children dates back many decades [28], it is only in the latest years that researchers have started to systematically study and develop principles for AI education [22]. In particular, researchers and teachers have created workshops and curricula to teach AI concepts to K-12 learners, i.e., from primary to high-school.

How to teach AI to K-12 learners is the main focus of this paper. This presents a systematic literature review of current tools and approaches to teaching AI in a playful manner to K-12 learners; the review also considers solutions for different learners but relevant for K-12 learners as well. Efforts have also been recently invested in defining initial guidelines for teaching AI in K-12, such as those by the AI4K12 Initiative [2, 33]. The AI4K12 Initiative is a joint project of the Association for the Advancement of Artificial Intelligence and the Computer Science Teachers Associations. It clusters guidelines in big ideas in AI and details what learners should be able to do according to different grades. The big ideas, relevant for this paper, are described in the following.

Perception and natural interaction. Artificial intelligent agents perceive the world using sensors, and they can then interact through actuators. Examples of perception go from touch-based sensors, to more elaborate forms of perception, such as speech recognition, computer vision, or any other form of perception. Examples of actuators are speakers or motors. Moreover, learners should be able to identify how to interact with intelligent agents, such as Alexa, understand how they interact with the environment, and possibly design and prototype their solutions.

Knowledge representation and reasoning. AI agents can maintain representations of the world and use them for reasoning. Examples are planning for self-driving cars, search in a graph representing communication routes, playing rule-based games such as chess and go. According to this big idea, learners should be able to design a model that represent a world, and reason on such representations.

ML. AI systems learn from data through ML. According to this big idea, learners should master basic terms and concepts pertaining to ML, besides the training and testing of basic ML algorithms, e.g., classification algorithms.

1.2 Motivation

AI is pervasive and is finding applications in a large number of sectors, e.g., automation, education, art. Teaching AI to younger generations is thus considered more and more relevant, as explained above. If teaching AI to students can usually rely on the fact that students have already basic computing knowledge and skills, that is not the case when teaching AI to K-12 learners. Moreover, the play dimension is often motivating for these learners: it can help enhance their attention, involvement, and understanding of abstract and complex concepts [11, 34].

In view of the growth of AI in different sectors and the need to educate younger generations to AI, it is thus not surprising that latest years have seen an increase in the number of playful tools for AI educational activities for K-12 learners. The literature distinguishes among game-based learning tools, gamified or gameful tools, or playful tools. Game-based learning tools usually refer to games designed with educational purposes. Gamified or gameful tools, more generally, aim at implementing ludic qualities or gamefulness, the experiential qualities characteristic for gameplay. Playful tools aim at affording so-called "paidic qualities", the experiential qualities characteristic for unstructured play [14]. In this paper, the distinction is blurred and "playful" is an umbrella term for them all.

Given the relevance of introducing K-12 children to AI, and of the play dimension in educational activities for them, this paper tackles the following questions:

R1. What are the available playful tools for teaching AI?
R2. How is their impact evaluated?

To answer such questions, the paper presents a systematic literature review in the major scholar databases. The aim of this systematic literature review is to analyse existing playful approaches to teaching AI to K-12 learners and compare them according to the type of tools adopted, target age, AI learning objectives, and evaluated impact.

This paper is thus structured as follows. Section 2 reports how the systematic literature review was conducted. Section 3 classifies and analyses articles resulting from the systematic search. The paper concludes by discussing them and elaborating on future work at the intersection of playful learning and AI.

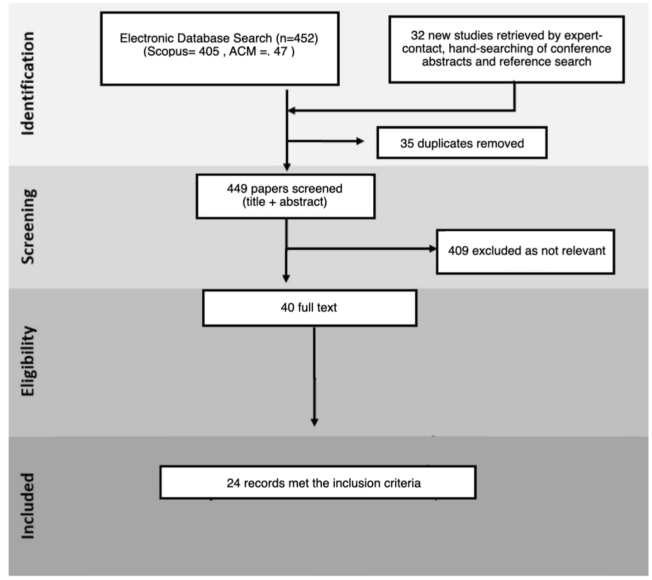

Figure 1: PRISMA workflow for the systematic review of this paper.

2 METHODOLOGY

This literature review is based on the approach "Preferred Reporting Items for Systematic Reviews and Meta-Analyses" (PRISMA), and proceeded as recapped in the flowchart in Fig. 1 [27].

Firstly, the overall goal was decided by considering work related to playful tools for teaching AI to children. Independently and iteratively, three researchers analysed related queries for searching major databases. The outcomes were jointly discussed and queries jointly revised. The final query was as follows:

```
( game OR play* ) AND ( "artificial intelligence" OR ai ) AND
( child* OR kid* ) AND ( educat* OR learn* )
```

The query was used to search for papers with those terms occurring in their title, keywords, or abstract, published from January 1, 2013, to January 31, 2023.

Next, the following major databases were considered: Scopus, ACM. These were chosen because they enable to search in the major Human-computer Interaction (HCI), Child-Computer-Interaction (CCI), and Technology Enhanced Learning (TEL) conferences and journals that publish relevant research related to children, interaction or education. The number of records identified by searching the major databases, without duplicates, was $n = 417$. Further papers were found through other sources, e.g., by expert contacts, hand searching in major conference abstracts related to HCI, CCI and TEL. In total, $n = 449$ papers were identified after removing duplicates.

The screening process started and the eligibility criteria were set. A paper was considered irrelevant, and hence to be excluded from the review, if it proposed an adaptive game exploiting AI or it used AI as a tool only, and not as learning subject, e.g., a paper that used AI in toys for teaching mathematics to children. A paper was considered relevant or potentially relevant, and hence to be included, if it considered how to teach AI to children and teens, including also teens beyond K-12 but younger than 18 years old.

The three researchers then split the papers in three buckets for coding them as relevant, potentially relevant or irrelevant. Their eligibility was assessed firstly by reading their title and abstract. In case this was insufficient for assessing them, papers were also fully read. Results were recorded in a spreadsheet which coded whether a paper was judged to be either relevant, potentially relevant, or irrelevant. Then researchers met to jointly discuss the coding outcome. All papers that had been coded as relevant were jointly discussed and the coding of researchers was jointly revised. Afterwards, each researcher was assigned to review 20% of papers which had been coded as potentially relevant or irrelevant by another researcher. No new revisions were judged necessary.

The final outcome resulted in $n = 24$ papers to consider as relevant or potentially relevant for this review: 20 were considered relevant, the others were considered potentially relevant. In the end, irrelevant papers were mainly those that used AI as a tool and not as a learning subject. All relevant papers were related to tools for playfully teaching AI to children or teens. Potentially relevant papers, which do not consider tools, were judged anyhow relevant for teaching AI to K-12 learners, e.g., papers that consider what to assess when teaching AI to K-12 learners. Relevant and potentially relevant papers are separately analysed in the following two sections.

3 RESULTS OF THE LITERATURE REVIEW: PLAYFUL TOOLS FOR AI EDUCATION

For analysing all relevant articles, researchers adopted the six-step iterative process by Braun and Clarke [8]: reading and familiarising with the articles, coding, generating themes, reviewing themes, defining and naming themes, and finally writing up.

The major final themes, which were agreed for classifying and analysing articles, considered the **types of tools** that articles presented. The first type is that of *phygital* tools, which combine physical elements such as play-cards, and digital elements such as programmable electronics. The second type is that of *digital* tools, such as chat-bots or Scratch-like programming environments. The last type is that of *unplugged* tools, which use no digital elements.

Other relevant themes agreed upon for analysis papers were what **AI is taught**, the **target age**, and **evaluation** of the impact of the tools. Table 1 recaps them and the subsections below analyse them, one per type of tools. When authors do not report the explicit target age neither in the design of the proposed tool nor in the evaluation, the table reports *not specified* in the `target` column. In case there is no evaluation, that is reported as *not specified* in the `evaluation` column.

3.1 Phygital Tools for AI Education

There are five tools which are classified as phygital. The first two, presented below, use block-based programming tools and card-based tools. One mixes unplugged and programming tools, again block-based, and it reports on the success of learners in training. The other two instead present so-called tangible tools, which embed electronics to interact with learners and teach AI. They address different target ages, and the evaluation ranges from informal reports of learning to more empirically-driven assessment of learning and engagement. All except one address ML (4 out of 5). Each article is briefly described separately in the remainder.

Hsu et al. [20] proposed `AI 2 Robot City`, a modified version of the `Robot City` unplugged card-based board game. Learners developed a smart phone app with the MIT App Inventor enhanced with an image recognition program that converts Robot city cards into a robot-car's movements. Learning was evaluated via an ad-hoc questionnaire comparing individual and collaborative learning; it seems that collaborative learning was more effective than individual learning.

Jordan et al. [21] proposed `PoseBlocks`, a suite of block-based programming tools based on Scratch which enable students to build compelling body-interactive AI projects in any web browser, integrating camera/microphone inputs and body-sensing user interactions. To support the use of PoseBlocks, the authors provided learners with scaffolding materials, such as PoseBlocks cards to show examples of block combinations, sample projects, and an ethical design support. Participants' engagement was evaluated by considering their final projects. According to what reported, learners successfully trained ML models on their own and proactively proposed projects with social impact.

The work by Bonani et al. reports on the design of tangibles for teaching how to search with a graph. The tangibles appeal to different senses so as to engage learners actively. Authors conducted a field study with their tangibles and 14–15 years old high-school learners, divided into two groups: one group used tangibles, the other used traditional means, namely, paper and pencils. The study results showed that tangibles were more engaging than in the traditional paper-and-pencil setting, and differences among groups are statistically significant [7].

Broll et al. [9] proposed an approach based on a combination of unplugged and programming activities in NetsBlox [10], an extension of Snap!, to help secondary students build deeper understanding of how AI/ML techniques work and how the machine actually learns. There is no report of learning gains or other related benefits for participants.

Scheidt et al. [31] present Any-Cubes, a prototype toy to enable children to explore ML and IoT technology. Any-Cubes consists of two physical wooden cubes which combine deep learning-based image classification and machine-to-machine communication. The focus is not on learning or related gains, which are not evaluated.

Table 1: Relevant papers related to playful tools to teach AI, considering the type of tools, the target age and evaluation.

Title	Ref.	AI	Target	Evaluation
5 Phygital tools				
Behavioral-pattern exploration and development of an instructional tool for young children to learn AI	[20]	ML (classification)	primary school	learning
PoseBlocks: A Toolkit for Creating (and Dancing) with AI	[21]	ML (classificaiton)	middle school	engagement
Touch, See and Talk: Tangibles for Engaging Learners into Graph Algorithmic Thinking	[7]	search algorithms	middle and high schools	engagement & learning
Beyond Black-Boxing: Building Intuitions of Complex Machine Learning Ideas Through Interactives and Levels of Abstraction	[9]	ML	high school	*not specified*
Any-cubes: a children's toy for learning AI	[31]	ML	*not specified*	*not specified*
10 Digital tools				
Teaching Conversational Robots in a Museum Exhibition with Interactive Surfaces	[13]	AI & ML	primary, middle schools	*not specified*
Learn to Machine Learn via Games in the Classroom	[40]	AI & ML fundamentals	primary, middle, high schools	players' attitude
Introduction to Machine Learning with Robots and Playful Learning	[26]	ML	primary, middle, high schools	engagement
Kids making AI: Integrating Machine Learning, Gamification, and Social Context in STEM Education	[30]	ML	middle school	learning
Introducing Children to Machine Learning through Machine Teaching	[15]	ML classification	primary school	*not specified*
Investigating a visual interface for elementary students to formulate AI planning tasks	[29]	planning, ML, and computer vision	primary school	engagement & usability
Empowering AI competences in children: A training program based on simple playful activities	[5]	AI literacy	primary, middle schools	*not specified*
What are GANs? Introducing Generative Adversarial Networks to Middle School Students	[3]	GANs	middle school	learning
ARIN-561: An Educational Game for Learning Artificial Intelligence for High-School Students	[39]	search algorithms	high school	learning
A Game Battle Platform based on Web-API for Artificial Intelligence Education	[17]	AI algorithms	high school	*not specified*
5 Unplugged tools				
Empowering AI Competences in Children: The First Turning Point	[6]	search algorithms, AI planning	primary, middle schools	engagement & learning
Teaching Artificial Intelligence to K-12 Through a Role-Playing Game Questioning the Intelligence Concept	[18]	AI literacy	primary, middle schools	awareness
GANs Unplugged	[38]	GANs	high school	engagement
The Development of Students' Computational Thinking Practices in AI Course Using the Game-Based Learning: A Case Study	[24]	AI	high school	learning
Data Detectives: A Tabletop Card Game about Training Data	[32]	ML training data	*not specified*	*not specified*

3.2 Digital Tools for AI Education

There are ten tools which are classified as digital. The majority of them is block based, and many address ML (6 out of 10). They cover all age ranges, and they are differently evaluated, mainly considering engagement and learning, which however seem to be differently defined. Each paper is described separately in the remainder.

3.2.1 Tools to teach ML. Candello et al. [13] proposed foundational AI concepts to children in a 30-minute hands-on playful experience designed for museums and community centres: learners were invited to teach biology, chemistry, and physics to three AI-based conversational robots. It aimed at making children understand that AI ML systems make mistakes and that can be corrected by knowledge acquired from human beings.

Zammit et al. [40] proposed `ArtBot`, a digital game to teach fundamental principles of AI and ML to primary and secondary school classrooms. The game narrative ask the players to retrieve art objects which are missing, and to train ArtBot in distinguishing between statues and paintings. Beyond anonymous data collected from log files, an online survey was also used to examine players' attitudes toward the game. Both learners and educators reported generally positive reception of the game, they found it relatively easy to understand how to play the game, that they would play it again, and that it helped them understand more about AI and ML. The responses on how fun the game was were fairly positive from all participants, reporting need for guidance and boredom as main issues. The manual image labelling in the supervised learning mini-game did not appeal to players, and the outcome of supervised learning did not vary enough with changes in the settings to hold players' attention. In addition, while the first few reinforcement learning levels were frequently played, the subsequent ones did not offer enough variety or novelty to retain players' interest.

Olari et al. [26] introduced, in a playful manner, supervised, unsupervised, and reinforcement learning using a block-based programming language in combination with the benefits of educational robotics. Their approach aimed at placing learners "in the algorithm shoes". K-12 learners were asked to modify weights in the neural networks and observe the effects on the simulated robot to experience how ML work in practice. Authors evaluated children's perception in terms of interest and perceived difficulty via questionnaires involving all the K-12 classes. As an overall outcome, the vast majority of learners found the topics engaging and easy to follow.

Sakulkueakulsuk et al. [30] proposed `RapidMiner`, a block-based interface to create ML models by a game-based approach. It encouraged learners to exploit emerging technologies, such as AI, for solving real-world problems. In particular, it focused on the exploitation of classifiers in the agricultural field, to recognise mangoes. Authors measured the impact of their approach in terms of learning experience by comparing pre- and post-workshop self-assessment questionnaires, and learning outcomes by checking the accuracy of the implemented classifiers. All the participants enjoyed the learning experience, and at least 11 out of 15 groups came up with a model that can accurately predict mangoes features better than randomly guessing, and the learning outcome improved by experience.

Dwivedi [15] explored the use of interactive ML interfaces, also known as teachable machines, for introducing ML to 7–13 years old children. There is no evaluation of any learning gain or other related benefits.

Park et al. [29] proposed `PRIMARYAI`, a block-based learning environment that enables upper elementary school learners to gain experience with AI-infused problem solving using in-game visual interfaces. For instance, learners have to specify AI planning tasks through initial states, possible actions, and goal states. Park et al. assessed the easiness of use of the platform and learners' engagement via screen and audio recordings concerning their interaction with `PRIMARYAI`. According to what reported, learners were very active and excited during the game, and they effectively formulated the AI planning tasks.

3.2.2 Other Tools. Baldoni et al. [5] presented EmpAI, a project that aims at empowering fifth and sixth-grade children in AI literacy. They identified four basic AI abilities, devised a training program based on such abilities and conceived an experiment to test the effectiveness of the training in promoting children's learning to play with and program the Codey Rocky robot with mBlock5, based on Scratch 3.0. The basic abilities are: to differentiate between syntax and semantics, to classify data, to improve planning abilities, and to reflect on test-operate-test-exit units. There is no evaluation of any learning gain or other related benefits reported in that paper.

Ali et al. [3] engaged 72 middle school students in a series of online workshops based on an online and team-based game to simulate how Generative Adversarial Networks (GANs) work and, then, on four existing generative AI web tools to generate media. Their proposal aimed at teaching middle school learners how GANs work and how they can create media using GANs. In particular, they experienced and reflected on the generator and the discriminator. During the assessment, learners were asked to reflect on their learning experience; they reported confusion and slight frustration in fully understanding the discriminator working mechanism.

Wang et al. [39] proposed `ARIN-561`, an educational game for teaching AI to high-school learners. In the game, learners play the role of a scientist who embarks on a scientific expedition, but crash-lands on an alien planet. In order to safely return home, the scientist begins exploring the planet to gather resources for repairing the broken ship while uncovering the mystery of the planet. ARIN-561 game focuses on developing concepts around classical search algorithms, such as Breadth-First Search and Greedy Search. ARIN-561 aimed at i) developing understanding of how AI algorithms are used to solve problems in the real world, ii) exploring strengths and weaknesses of AI algorithms to choose among them opportunely, iii) gaining high-level understanding of how each AI algorithm works. Wang et al. evaluated the gained knowledge via pre and post-questionnaires. According to what reported, there was a positive increase of AI knowledge, statistically significant only among participants who completed at least half of the game.

Han et al. [17] invited teenagers to program bots in Scratch to learn AI theory and practice AI algorithms. There is no clear report of learning gains.

3.3 Unplugged Tools for AI Education

There are five tools which are classified as unplugged. The first two use card-based tools and, as for the evaluation, only the first reports observations on understanding. The others use role-playing games (the first two) or adapt an existing AI course to senior high-school students with a game-based approach. They address different ages, and what is evaluated differs in each case.

Baldoni et al. also designed an experiment for their EmpAI project to test the effectiveness of the training in promoting children's learning of AI [6]. For each of the four basic abilities described above, they designed an unplugged card-based playful activity for K-5 and K-6 learners. According to the reported observations, there were differences in terms of understanding of the activities and engagement according to the activities themselves (e.g., planning versus classifying) and the school-grade.

Henry et al. [18] proposed instead a role-playing game, inspired by the game "Guess Who?", to teach to 10–14 years old learners the basic concepts of ML. Learners take on the role of a developer, a tester, or an AI. In groups, the children's mission is to create an AI capable of identifying an animal based on simple questions. By playing the game, children are expected to understand that there is always a human behind an AI system and should change their representation of AI. This change was measured by pre and post questionnaires and observations. According to what reported, the proposed workshops partially succeeded in convincing participants of the role plaid by developers in making machines intelligent.

Virtue [38] proposed a classroom activity to introduce generative adversarial networks (GANs) to secondary school students. It encouraged learners to physically and collaboratively act as the various components of a GAN, by splitting participants in different groups with different roles in GANs. According to authors' report, learners successfully completed the GAN simulation independently from their previous experience in AI and were extremely engaged during the entire workshop.

The work by Ma et al. reports a study that presents an AI course, named "Challenging Tic-Tac-Toe", for senior high schools. According to what reported, the game-based learning approach to AI helped students master, in particular, AI subject knowledge, and it enhanced learning interest, motivation, self-confidence [24].

Finally, Solyst et al. [32] proposed `Data Detectives`, a multiplayer 2–6 card-game to enable youth and families to understand training data in ML. There is no evaluation of any learning gain or other related benefits.

4 RESULTS OF THE LITERATURE REVIEW: OTHER FINDINGS

Other papers do not present playful tools to teach AI, but they were anyhow judged potentially relevant because they can help further tackle the question of how to evaluate playful tools for teaching AI to K-12 children. They are described in details below, and recapped in Table 2, by considering the target age and the evaluated impact dimension.

Burleson et al. [12] developed an Active Learning Environments with Robotic Tangibles (ALERT) and an analogous on-screen virtual spatial programming environment (Robopad) for engaging children into a free play and open-ended learning activities. The paper reports a study with 9–6 years old children playing and interacting with both the physical ALERT and digital Robopad robots, and compared their collaborative engagement in spatial programming. Results reported that both systems afford opportunities for young learners to engage in spatial programming, creating improvisational and sequential programs that mediate interactions between the environment, robots and humans in responsive and creative ways. The work demonstrated innovative opportunities for advancing mixed reality spatial programming activities as a new form of computational thinking engagements that fosters collaborative, creative, and highly motivating experiences in formal and informal environments.

Vazhayil et al. [37] reported the AI curriculum and pedagogical approach adpopted for delivering AI training to Indian secondary school computer science teachers. They conducted a study with 34 teachers who participated in the AI teacher training programs. Results from the semi-structured interview to the teachers report the perceived challenges of the teachers in relation to intersectional factors such as infrastructure, pedagogy, and culture in the context of Indian schools.

Van Brummelen et al. [36] reported a study with middle and high school students for investigating how perceptions of a conversational agent like Alexa change through the programming of their own conversational agents. After a week-long workshops, authors found that students felt Alexa was more intelligent than before the study, and they felt closer to Alexa. As a final recommendation when designing conversational agents for learning contexts, the authors recommended that designers carefully consider personification, transparency, playfulness and utility.

Finally, Duri et al. [23] explored how to foster learning about AI with family groups in informal learning environments. The authors developed three studies, ranging from the steps and practices of ML to understanding knowledge representation. They investigate the types of dialogue the family groups engage in when learning about AI and how to design activities to facilitate family group learning about AI literacy competencies in this context. The results from the analysis of dialogues were used to reflect on, update and revise existing principles for designing AI literacy educational interventions.

5 DISCUSSION AND CONCLUSIONS

AI has a considerable impact on the development of our societies and is part of smart devices that young learners use. Researchers and educators are thus encouraged to make young learners aware of how to interact responsibly with AI, and to understand how it works. This paper focuses on K-12 learners. Since playful approaches have been widely exploited in education to engage them in learning, it is relevant to understand whether and how playful tools are used to teach AI to K-12 learners. This paper presents a systematic literature review addressing the following related questions: (**R1**) What are the available playful tools for teaching AI? (**R2**) How is their impact evaluated?

The review considered scientific contributions published since 2013 (in the latest 10 years), proposing playful tools to teach AI to K-12 learners. The remainder discusses the outcomes of the review, in relation to the two aforementioned research questions. Starting from it, it also discusses possible future directions of work, considering research in HCI and, specifically, CCI for education. It concludes by analysing the main limitations of the presented review.

5.1 R1: Available Playful Tools

5.1.1 AI Areas.

Current status. Among all AI areas, ML has received the most attention in the latest decade [20]. The same trend is observed in the analysed contributions: 10 of all the tools focus on ML, and

Table 2: Potentially relevant papers

Title	Ref.	Target	Evaluated dimensions
Active Learning Environments with Robotic Tangibles: Children's Physical and Virtual Spatial Programming Experiences	[12]	primary school	collaboration and creativity
Focusing on Teacher Education to Introduce AI in Schools: Perspectives and Illustrative Findings	[37]	school teachers	intersectional factors, e.g., culture
"Alexa, Can i Program You?": Student Perceptions of Conversational Artificial Intelligence before and after Programming Alexa	[36]	high school	personification, transparency, and utility
Family Learning Talk in AI Literacy Learning Activities	[23]	family groups (6–18+ y.o.)	principles for designing AI literacy educational interventions

particularly on classification. This trend is even more evident in the group of papers concerning phygital tools: 4 out of 5 address ML.

Future work. In the future, further topics could be introduced to K-12 learners, such as generative algorithms, covered by 2 tools only, or deep learning, apparently not covered by the reported contributions. It is worth noting that deep learning includes generative algorithms, besides neural networks, transformer networks, autoencoders.

Last but not least, AI is a big, continuously evolving field. As the introduction shows, it includes, e.g., search, knowledge representation and reasoning, ML. What kind of AI literacy is taught should be reflected over in relation to the context and the evolution of AI. As the review highlights, in the future, principles for AI interventions should be crafted specifically by considering the target age and environment. The AI4K12 initiative, reported in the introduction, is an attempt in that direction [33]. Moreover, the AI work evolves rapidly and specialises according to the application field (e.g., computer vision versus natural language processing). Hence, it is speculated that further principles, approaches and tools will be required in the future to empower K-12 learners in relation to novel forms of AI.

5.1.2 Types of Tools and Age Range.

Current status. According to the AI4K12 Initiative, children of all levels, from primary to high school, are expected to be able to cope with central paradigms of AI. As Table 1 shows, there are phygital, digital or unplugged tools to teach AI to K-12 learners of diverse grades.

The reported playful tools are mainly digital (10 out of 20). Several of them extend block-based programming environments to support building projects that incorporate various AI programs or ML models. They are either ad-hoc and custom defined during a project, or they exploit well-known programming environments, such as Scratch, App Inventor and Snap. Two phygital tools also use block-based programming tools with card-based material, whereas others adopt tangible tools. When unplugged tools are used, they mainly propose card-based material or role-playing game material.

Overall, there seems to be lack of equal efforts in the direction of phygital or unplugged tools versus digital tools for teaching AI to K-12. This is rather surprising, considering in particular that years of research in CCI have shown the importance of promoting different learning modalities (e.g., kinaesthetic, related to movement) and of the physical dimension of tools for younger learners, e.g., primary-school learners and pre-school learners. The physical dimension of physical tools and the lack of screens, as in so-called head-up solutions, often yield spontaneous social interactions and discussions face to face, which help promote the development of social skills [1, 19].

Future work. Future work concerning tools for teaching AI may consider to go beyond digital tools, considering more the physical dimension, and the target of pre-school children. The systematic literature review by Bakala et al. provides a comprehensive overview of tools that enable preschool children to practice their Computational Thinking skills and build programs that include control structures, and it analyses empirical evidence of the usage of these tools, as this paper did for playful tools for teaching AI to K-12 learners [4]. They conclude that there are many existing tools that enable children to learn programming with a structured approach, however, it is not clear which tools and activities are the most appropriate because of lack of clear empirical evaluation studies. This leads to the next research question, related to the evaluation of the impact of the tools for teaching AI to K-12 learners.

5.2 R2: How to Evaluate their Impact

5.2.1 Engagement and Learning.

Current status. Papers concerning tools for teaching AI playfully, which cover the evaluation phase, tend to focus either on learning or engagement. Not all surveyed papers evaluate the impact of the proposed playful tools; 6 do not report clearly any evaluation. Learning through the tools is assessed via standard or mainly ad-hoc questionnaires, observations, or reflections on users' experience. Engagement is usually measured via questionnaires or an analysis of the recorded activities. An exception is the paper by Bonani et al. which considers both engagement and learning, and it assesses them empirically in different manners [7]. In particular, engagement is assessed systematically via a specific observation protocol and a coding scheme which considers the collaborative dimension of engagement, besides a self-report questionnaire.

Future work. Based on the outcome of the analysis, it is recommended that further effort be devoted to assessing engagement, AI learning, and their correlations, also in the long term. Moreover, as the review shows, there are different tools for teaching AI to K-12 learners, but the assessment of their impact differs. Future research should consider standardized instruments for evaluating the impact in terms of learning and engagement, which would allow for a comparison of the impact of the tools in different contexts and used by different learners.

5.2.2 Further Dimensions.

Current status. The papers reported as potentially relevant, besides research in CCI for education can provide ideas for considering different dimensions in evaluating the impact of playful tools for teaching AI to K-12 learners. As in the work of Bonani et al., also in other work, classified as potentially relevant in this paper, the collaborative dimension of learning and engagement emerges as relevant. Another aspect is creativity, in relation to what products learners create with the given tools. Others highlight the importance of considering also intersectional factors in the planning of a learning activity and analysis of results, such as the socio-economical background of participant children, which resonate with the need of comparing the impact of tools in different contexts.

Future work. As in the case of the systematic literature review of CT tools by Bakala et al. [4], also in the case of the review of this paper, it emerges that future efforts should also evaluate whether the given tools can be used in school settings. School settings, in fact, impose their own constraints on the development of tools for children, e.g., classrooms are multi-dimensional and simultaneous and that impacts on the development on conversation-based tools for teaching children in class [16]. The impact of tools over time on the development of children, overall, is one of the aspects least evaluated and probably one which requires most attention in general according to the CCI literature [19].

5.3 Limitations

The review was done following the PRISMA methodology and reporting the performed steps in as much details as needed. Limitations are also related to the considered online sources, which may hamper the generality of our findings. In such cases, we tried complementing findings with other information sources, like experts.

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