Technologies for Children's AI Learning: Design Features and Future Opportunities

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Abstract

With the growing integration of AI into daily life, various technologies have been developed to teach children about AI. However, differences in their designs highlight the need for a thorough understanding of these tools to make the most of current technological resources and guide the effective development of future learning tools. Through a systematic search, we identified 64 different AI learning tools for children and analyzed their design features, including both static design features (i.e., presentation formats and learning content) and interactive design features (i.e., learning activity types and design features that potentially enhance the effectiveness of the activities). Our findings reveal the current trends and gaps in the design of children's AI learning technologies. Based on these insights, we reflect on future design opportunities and provide recommendations for creating new, effective learning technologies to advance AI education for the next generations.

CCS Concepts

• Social and professional topics → Children; **K-12 education**; **• Human-centered computing → Interaction devices**; **• Applied computing → Interactive learning environments**; **• General and reference → Design**.

Keywords

AI literacy, AI learning tool, Learning technology, Design

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1 Introduction

Artificial intelligence (AI) nowadays plays an active role in all life aspects, from personalized music recommendations [8] and smart vehicles [92] to medical decision-making [125] as well as prominent Generative AI (GenAI) systems recently like ChatGPT and DALL-E. Recognizing AI's growing significance, governments [114], industries [108], and academics [50] have urged teaching AI to the public, especially young people, to prepare them for the AI-driven era. As such, mainly in the last five years [66], numerous initiatives have emerged to integrate AI into children's education. Indeed, proficiency in AI is now seen as a cornerstone of technological literacy, allowing children to make informed decisions about AI use and engage in discussions on its regulation and governance [17]. Besides, AI education provides young people with the mindsets and skills necessary for future job markets where collaboration with AI is crucial for efficiency, innovation, and competence [133]. Moreover, early exposure to AI can also ignite children's curiosity and interest in higher education and careers in technical fields, ultimately fostering future technological advancements [137].

Acknowledging the value of early AI education, more and more technologies have been designed to support children's AI learning experiences and outcomes, such as online platforms for developing machine learning (ML) models [16, 62] and interfaces to visualize AI workflows [64, 98]. Such technology-based tools[1] make complicated and abstract AI concepts more tangible, accessible, and engaging than conventional courses. For example, interactive web-based apps allow children to observe how neural networks process and recognize sketches [64]. These tools also extend AI education beyond traditional classrooms. For instance, Tseng and colleagues [111] designed a tablet-based app to support children and parents in collecting data and training AI models together at home, providing learning opportunities and knowledge retention outside of formal education settings. The positive results of these tools in improving children's AI learning outcomes [9] and experiences [79] suggest that technologies have great potential for early AI education.

Despite the growing number of AI learning technologies for children, noticeable disparities exist in their design. These tools vary widely in presentation formats [7, 12], areas of AI learning content [28, 61, 90], and learning activities [2, 5]. Although several surveys have explored AI learning technologies for children, they often focused on certain tool types (e.g., tools aimed at secondary school students [77]), only analyzed specific design features (like presentation formats and learning activities [126]), or covered AI curriculum in their scope without dedicated tool design analysis [66, 105, 106]. Some surveys even include tools not directly addressing AI concepts [58]. Furthermore, few studies have examined these tools from a design perspective [11], an important perspective

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[1]We used *technology* and *tool* interchangeably in this paper to improve lexical diversity. While the term *tool* may include a wider scope (e.g., non-technology-based instruments), we only focus on technology-based tools with electronic components (i.e., computer artifacts) in this study.

required for informing the creation of new technologies that effectively promote children's AI education. This lack of comprehensive understanding of current AI learning tools and their design can lead to missed opportunities for fostering AI literacy among young people, which is increasingly critical due to the growing prevalence of AI applications (e.g., ChatGPT [3]) and their societal impacts. AI literacy is essential not only for future computer scientists and designers seeking technical expertise but also for all children to understand AI's implications, navigate ethical dilemmas, and respond to challenges involving harmful intentions [63]. Additionally, as AI literacy nurtures transferable skills like critical thinking [104] and collaborative problem-solving [119], failing to utilize existing tools effectively may hinder children's ability to address broader challenges. Moreover, without a thorough overview of AI learning tools, educators and designers risk overlooking key design features that characterize existing technologies and can serve as the reference for designing new tools to cater to diverse learning needs. Hence, a comprehensive survey of AI learning tool design is imperative to empower learners, educators, and designers to fully utilize current educational resources and facilitate the creation of more accessible and engaging tools that equip children with the competencies necessary in the AI-centric future.

To bridge the gaps and promote children's AI education, this study seeks to address the research question: ***How are technologies designed to support children's AI learning?*** To answer this, we systematically collected and examined 64 existing AI learning tools for individuals aged 18 and below, drawing from research articles and recommendations by AI-related academic communities (e.g., *INSPIRE Engineering Gift Guides* [35, 36]). We focus on examining these tools' design features, i.e., their elements or characteristics that contribute to children's AI learning experiences and outcomes. Our analysis is structured around three design feature dimensions identified from previous reviews of AI and STEM learning tools (e.g., coding kits [130]), which typically comprise both static and interactive features. Static design features—elements that remain constant regardless of children's interactions—encompass *presentation format* (how AI learning materials and activities are presented to children [77, 99, 130]) and *learning content* (the topics that the tool aims to teach [77, 99, 105]). Conversely, interactive design features, which display or change only based on how children interact with tools, concentrate on *learning activity* (types of activities the tool engages users to learn about AI and design features enhancing such activities by aligning with children's effective learning patterns [106, 116, 126]). This framework, which incorporates both static and interactive design features, was employed because it effectively captures the visual and activity elements of a learning kit, offering a systematic analytical approach to better understand the design of AI learning tools for children. We also examined these tools' target age groups and the interconnections between the three design features and age groups to determine which content is taught through which activities and formats for various ages. This holistic approach aims to guide the selection, use, and creation of AI learning tools tailored to diverse educational demands for children. Our findings show that current tools are designed to teach three sets of content (AI awareness, mechanics, and impacts) through four types of activities (conventional instruction, experiencing, modifying, and creating) and two formats (virtual and hybrid tools), alongside four groups of design features that may enhance children's active, engaged, meaningful, and socially interactive learning of AI [41]. Based on these findings, we highlight the current gaps in children's AI learning tool design (e.g., underrepresented or missing AI concepts) and reflect on future opportunities for designing more effective AI learning technologies.

Our contributions are twofold. First, we present a systematic overview of children's AI learning tools endorsed by scholarly communities, which serves as a valuable reference for educators and parents to identify, evaluate, and select tools for children. A list of analyzed tools and their design features are shown in Table 3 in the appendix. Second, we highlight the existing trends and gaps in children's AI learning tool design, providing inspiration and guidance for creating effective tools to fuel early AI education through technology design.

2 Related Work

We aim to survey existing technologies and examine how they are designed to support children's AI learning. Accordingly, this section reviews the literature on the design of learning technologies, the current state of children's AI education, and existing surveys on children's AI learning tools.

2.1 Design of Technologies for Learning Purposes

The global reach of the Internet and mobile devices has led to a surge in hardware and software to support learning, i.e., learning technologies [40]. From massive open online courses [60] and dynamic visualizations [86] to interactive educational games [81], these technologies have revolutionized the educational landscape by enhancing the interactivity of conventional instruction. For example, mobile apps provide immediate, contingent feedback that is not always available in traditional classrooms [76], which contributes to more dynamic and engaging learning experiences. Besides, digital learning tools, such as online programming environments (e.g., Scratch), provide easy access to and retention of learning materials regardless of physical location, thereby supporting educational continuity beyond formal schooling.

To harness the vast potential of technologies, efforts from different domains have been dedicated to guiding the design of technology-based tools to promote effective learning. Among these efforts, Hirsh-Pasek et al. [41] synthesized decades of research from learning sciences, an interdisciplinary field that merges insights from psychology, cognitive sciences, and education to understand how children learn most effectively. They then distilled four conceptual principles—engaged, meaningful, and socially interactive learning—which are widely supported by well-established theories and empirical evidence, and generated four sets of guidance for integrating these "four pillars of learning" into educational app design. The pillar of ***Active Learning*** highlights that the app should be designed to foster children's active exploration of new ideas by "minds-on tasks" that require intellectual efforts (e.g., critical thinking and problem-solving). This concept is rooted in the constructivist theory [87], which posits that individuals construct knowledge of the world through interactions with their surroundings and reflections on such experiences, viewing learning as an active process rather than passive information reception. ***Engaged Learning*** emphasizes the need to maintain children's attention to learning activities, which could be achieved by providing materials at appropriate challenge levels and offering immediate feedback. This pillar can be traced back to Fredrick and colleagues' review of school engagement [37], which concludes that children are more likely to retain information and gain a deeper understanding of learning content when engaging behaviorally (e.g., following rules), emotionally (e.g., experiencing affective responses), and cognitively (e.g., showing flexibility in problem-solving) in learning activities. ***Meaningful Learning*** focuses on incorporating new information into children's existing knowledge frameworks to facilitate understanding and retention, like embedding learning activities within learners' familiar contexts. Its philosophical underpinning [10] distinguishes itself from rote memorization, contending that effective learning can occur when new concepts are assimilated into children's existing cognitive structures, allowing them to derive personal significance from what they learn. Lastly, the ***Socially Interactive Learning*** pillar encourages creating environments that promote group interactions for information exchange and collaboration. This principle is grounded in social development theory [118] and natural pedagogy [20], which underscore children's innate tendency to learn through social cues, dialogues, and collaborative problem-solving [46]. With a robust theoretical foundation and empirical backing, these "four pillars" constitute a holistic understanding of children's effective learning patterns. As such, we will employ this framework to identify design features that potentially enhance children's learning effectiveness in the examined AI learning tools.

2.2 AI Education for Young People

The initiatives to educate children about AI, while having existed for over five decades, have rapidly evolved in recent years due to the growing prevalence of AI [66], especially recent GenAI. Accordingly, various AI learning interventions have been developed for children at different developmental stages, ranging from kindergarten [120] to secondary school [77]. These programs often aim to equip young learners with AI knowledge and skills in three critical areas: AI awareness, AI mechanics, and AI impacts, which form the core content of existing AI curricula. Learning materials focusing on *AI awareness* typically address the conceptual knowledge of AI, including basic definitions of AI [6], its applications in various areas [56], and its historical development [78]. The *AI mechanics* area delves into the technical process behind AI, emphasizing aspects such as common AI input and output types [32], machine learning styles (e.g., supervised learning [79]), representative algorithms [34], and basic steps to train AI models [33]. The *AI impacts* area seeks to raise awareness of AI's societal and ethical impacts [13] and aims to shape children into responsible AI users and designers [107].

Notably, many technologies have been designed, developed, and deployed to facilitate teaching these AI concepts. For example, Williams et al. [121] developed an AI-powered robot to engage learners in child-AI joint drawing, which helps cultivate AI awareness by providing a tangible example of AI applications. Similarly, websites like *Teachable Machine* [16, 62] enable children to train classifiers using their own images, texts, and speeches, providing a hands-on experience of supervised learning. Meanwhile, Minecraft's video game *Hour of Code: Generation AI* [28] addresses AI impacts by guiding children to understand and solve four representative AI ethical issues by fixing the back-end codes. These technologies have generated new momentum for AI education and indicated the potential of technology design to support children's AI learning. However, considering the diversity of these tools, there is a pressing need for a systematic overview of existing tools and structured guidelines to aid designers in making evidence-based, informed decisions when developing new tools (e.g., selecting appropriate learning content, learning activities, and presentation formats for children with different learning demands)—a key gap in advancing children's AI learning tool design.

2.3 Existing Surveys on Children's AI Learning Tools

Following the proliferation of children's AI learning tools, multiple surveys have been conducted to understand this emerging research landscape (e.g., [11, 38, 58, 66, 77, 99, 105, 106, 116, 126]). These studies, on one hand, focus on describing design features of a particular type of learning technologies, such as tools intended for a certain age group (e.g., secondary school students [77]) and those used in a specific geographical region (e.g., Asia-Pacific [106]), or emphasized tools with specific presentation formats (e.g., digital games [38]), tools that teach certain content (e.g., design components of machine learning models [11]), and those that engage children in specified activities (e.g., creating custom AI models [116]). On the other hand, other surveys take a broader approach by examining a wide range of tools across multiple design feature dimensions, such as presentation format (e.g., robotics [99]), learning content (e.g., neural networks [66]), and learning activity (e.g., direct instructions [126]). However, these features are rarely analyzed collectively. Since the effectiveness of learning activities often depends on the age-appropriateness of the content and how the material is presented to children [65], it is crucial to approach these dimensions jointly to reveal the synergies and interdependencies that shape the outcomes of AI learning tools. This holistic overview facilitates cohesive design decisions across dimensions, ensuring they work together to meet diverse educational needs—insights often overlooked in prior surveys examining each dimension in isolation.

Additionally, existing surveys often include tools that do not directly address AI concepts, such as coding environments focusing on teaching computational skills rather than AI knowledge [58]. Several studies even encompass both AI instructional units (e.g., coursework and workshops without tool usage) and AI learning tools in their scopes [66, 105, 106], making it difficult to disentangle specific insights into tool design. Furthermore, very few studies have examined children's AI learning technologies from a design perspective, which is crucial for guiding the development of more effective learning tools. To the best of our knowledge, only one study has explicitly addressed how learning tools can be designed to teach machine learning pipelines [11], highlighting a significant gap in design guidelines for children's AI learning technologies. In short, the lack of systematic understanding of AI learning tools and their design features may impede educators, parents, and children from fully benefiting from existing resources and constrain designers and developers from creating new, more effective tools for children. Therefore, the current study seeks to comprehensively survey and examine the design features of AI learning tools for children.

3 Methods

We followed the *PRISMA* [80] protocol to systematically collect and examine existing AI learning tools reported in research articles and suggested by academic communities in AI and related domains. This section details our methods to search, screen, and analyze these tools.

3.1 Searching and Screening Tools

To identify children's AI learning tools reported in research papers, we conducted a systematic search in five digital databases that cover main literature sources in computer science, engineering, and learning sciences: *ACM Digital Library*, *APA PsycInfo*, *ERIC*, *IEEE Xplore*, and *Web of Science*. Our search query was guided by keywords extracted from the abstracts of 10 papers focused on designing AI learning technologies for children, i.e., [1, 11, 16, 39, 43, 51, 64, 110, 119, 141]. We organized these keywords into four clusters based on each tool's educational goal (e.g., *AI*), the activity it supports (e.g., *learn*), target learner (e.g., *youth*), and product type (e.g., *interface*). Additionally, we included terms related to the contribution type (e.g., *design*) to focus on papers about designing rather than using AI learning tools. Our search comprised exact terms (e.g., *artificial intelligence*), common abbreviations (e.g., *AI*), and plural forms with an asterisk (e.g., *child**). Lastly, we linked all separate terms under each group using the Boolean operator OR and combined all five groups using the Boolean operator AND, leading to our search query:

> {*"artificial intelligence"* OR *AI* OR *"machine learning"* OR *ML*} AND {*comprehen** OR *model** OR *learn** OR *teach** OR *understand**} AND {*app* OR *application* OR *interface* OR *platform* OR *tool*} AND {*child** OR *pupil** OR *student** OR *youth*} AND {*creat** OR *design** OR *develop**}

We conducted our initial search in paper abstracts on August 26, 2023, and obtained 3,700 returns. On March 27, 2024, we carried out an additional search using the same databases and search terms with a publication date filter to capture the publications since our initial search. This supplementary search yielded 732 more results, raising the total to 4,432. To broaden our scope, we employed snowball sampling by examining the references from 10 surveys on children's AI education [11, 38, 58, 66, 77, 99, 105, 106, 116, 126] and the tools mentioned while not analyzed in these studies (e.g., AI lessons by Minecraft [25–30]). We also reviewed the 2022 and 2023 *Purdue INSPIRE Engineering Gift Guides* [35, 36], which recommend tools and books for children's learning in engineering-related domains [74]. This effort added 689 returns, resulting in a total of 5,121 items for screening.

Table 1 presents our four inclusion and exclusion to screen tools: learning goal, target population, contribution type, and return presentation. We used a two-stage screening process to select the tools within our analytical scope, consistently applying the same process and criteria throughout both stages. First, we performed a broad filter based on paper titles, abstracts, and tool descriptions, which reduced our results to 125 items for further screening. Then, with a detailed review of each full-text paper, tool descriptions, and supplementary information (e.g., Educator Guides [25]), we identified 64 distinct AI learning tools from 80 results for analysis (see Figure 1 for the detailed process).

3.2 Analyzing Tools

We employed content analysis [54] to extract and analyze the design features of the identified tools as detailed by the paper authors or tool developers. We selected this method over direct interaction with each tool as more than half of these tools (51.6%) were not publicly available, limiting our access to first-hand experience; for publicly available tools, the first author did interact directly with them to deepen our analytical process. This approach has also been widely employed in existing surveys on the design of children's learning tools in AI [105, 106] and other STEM areas, e.g., computer programming [129, 130], proving its validity and suitability for understanding learning tool design when direct access is restricted.

Our analysis focused on three design feature dimensions, covering both static (presentation format, learning content) and interactive (learning activity). We also explored target age groups and the interconnections between three design features and age groups. Note that we did not delve into students' learning outcomes due to the lack of standardized evaluation methods [9, 111], the absence of empirical evidence [25], and variability in outcomes based on learner characteristics and contexts [65]. Nevertheless, to present a comprehensive overview of current tool design and guide

Table 1: Tool inclusion and exclusion criteria

Dimension	Inclusion Criteria	Exclusion Criteria
Learning goal	The tool focuses on AI learning.	The tool does not focus on AI learning.
Target population	The tool aims at children aged 18 and below.	The tool is designed for the other age groups (e.g., college students).
Contribution type	The article or description introduces the design of an original tool.	The article or description focuses on the use of an existing tool.
Return presentation	The article or description is in English.	The article or description is in other languages.
	The tool is cited in a peer-reviewed research paper or an academic community related to AI.	The tool is not cited in a peer-reviewed venue or an academic community in AI-related subjects.

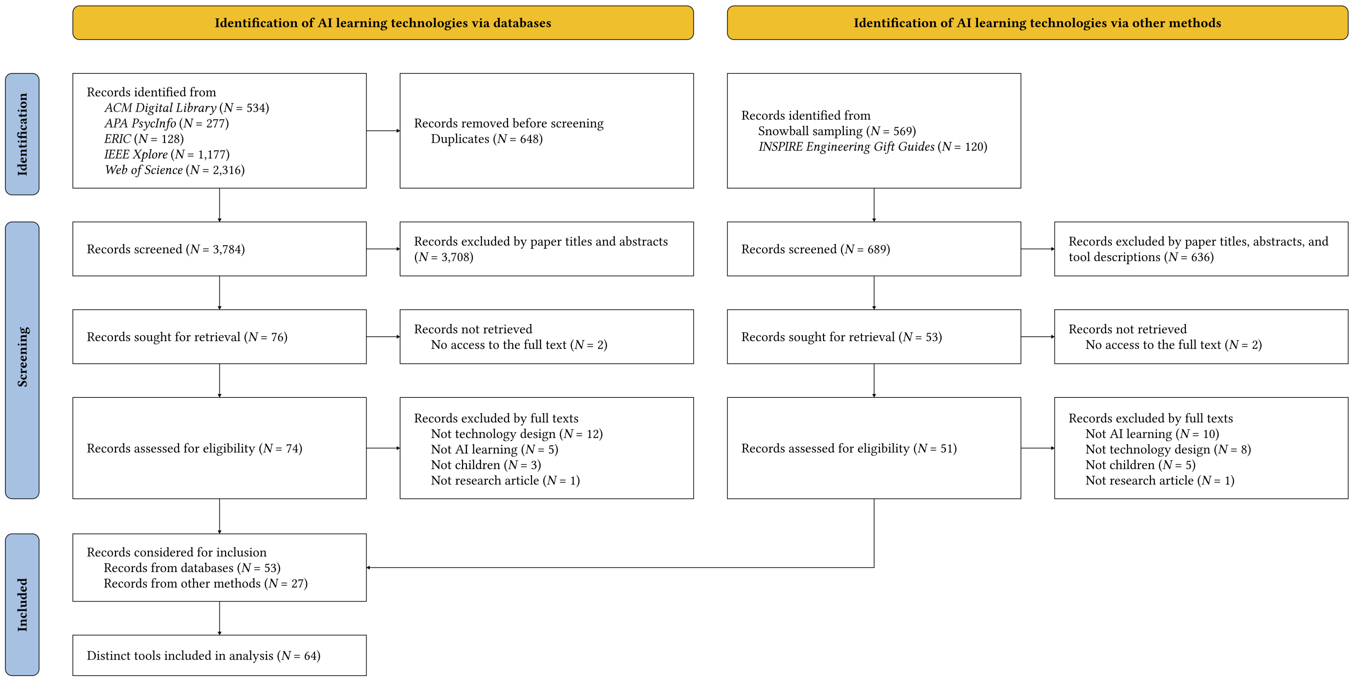


Figure 1: Tool searching and screening process. Adapted from [80].

iterations of future tools, we examined methods for assessing the effectiveness of empirically evaluated tools.

We used the qualitative analysis software MAXQDA [68] to systematically identify and examine the textual content on the tools' design features, target age groups, and assessments. This involved analyzing tool descriptions from the methodological sections of included articles, which detailed design processes and principles [12, 121] and the tools' components, incorporated learning materials, and sequential steps of learning activities [89, 111]. We also analyzed the texts addressing user studies, which documented children's interactions with the tools and offered insights into practical design details, as well as target age groups and assessment methods. To enhance data coverage, we included tool descriptions from other sources (e.g., Minecraft's educator guides and curriculum overviews [26]), which added AI topics addressed and breakdowns of the tools' learning activities. The entire coding process was performed manually to ensure a nuanced understanding of the data. After this initial coding, we grouped all codes into three codebooks (see the codebooks of presentation format, learning content, and learning activity in the supplementary file), each tailored to one of the three design feature dimensions, setting the stages for more focused analysis under each dimension.

For the dimension of *presentation format*, we consulted Yu and Roque's [129, 130] taxonomy that classified children's coding kits into three categories: physical kits (entirely tangible), virtual kits (software applications without physical components), and hybrid kits (combining both physical and virtual elements). We assigned each included AI learning tool to one of these categories and inductively coded each tool's components, merging those with similar functions into broader themes. For instance, virtual web apps that visually demonstrate the workflows of k-means clustering [119] and neural networks [64, 98] were grouped into the theme "AI process visualization tools" within virtual tools. For hybrid tools, we considered their physical and virtual components as a cohesive whole to reflect children's integrated interaction with them. For *learning content*, we started with deductive coding, identifying the texts related to the three core areas of AI education—AI awareness, AI mechanics, and AI impacts—based on the literature on children's AI education (see Section 2.2). We then switched to inductive coding to organize detailed learning content within each area, labeling AI concepts in the extracted texts and grouping similar ones into larger themes. For example, "AI implication" and "responsible design" were grouped into the theme "AI impacts." This open, axial coding process continued till all extracted texts were analyzed to ensure non-overlapping themes.

Regarding design features of *learning activities*, we first used an inductive coding strategy to identify descriptions of activities involving the tools. These activities were then grouped by their ultimate goals, e.g., enabling children to observe a pre-trained AI model's workflow [64, 98] or to train a new model from scratch [16, 62]. Similar goal-oriented activities were merged and appropriately named, resulting in four activity types: learning through conventional instruction, experiencing, modifying, and creating. To identify the design features potentially enhancing the effectiveness of these activities, we examined each tool's design through the "four pillars of learning" [41] to seek the features facilitating students' active, engaged, meaningful, and socially interactive learning. Similar to our process of analyzing tools' learning content, we first deductively located the initial codes matching the conceptual definition of each pillar. Then, we followed a bottom-up approach to inductively coding the identified features and relevant texts within each pillar, generating the codes for design features that may foster effective learning activities, such as *"connection to personal history."* We compared these codes, merged and renamed similar ones, and created higher-level themes repeatedly. This iterative process continued until all our initial codes were thoroughly analyzed and our final themes adequately reflected the coding results.

For target age groups, we categorized each tool's intended learners into five key developmental stages [87]: kindergarten, lower primary grades, upper primary grades, middle school, and high school. To accommodate different educational structures across regions and countries, we referenced the national education systems related to the tools' development [19]. For tools without specified age groups, we inferred target ages based on participants who successfully engaged with the tools and exhibited positive AI learning outcomes (e.g., completing AI projects [139]). Next, we explored the interconnections among design features and target age groups, focusing on 1) the connection between learning content and activities, namely, which activities the tools support for teaching a certain area of AI knowledge, 2) the alignment of presentation formats with specific activity types, and 3) presentation formats, learning content, and learning activity types designed for each age group. Lastly, we analyzed the assessments of included tools from user studies, focusing on assessed variables (e.g., learning outcomes [9]) and assessment methods (e.g., project assessments [140]).

Two authors participated in the data analysis. The first author generated the initial codes, while the second author contributed to analyzing, reviewing, and refining all codes and themes. The codebooks were consistently updated throughout this iterative process. Then, a research assistant with qualitative analysis experience—who was not part of data analysis—coded nine randomly sampled papers on six distinct tools with the themes generated from the data analysis. The coding results were compared to those finalized by the two authors and showed *almost perfect* agreement (κ = .82) [70], indicating the high reliability of our analysis.

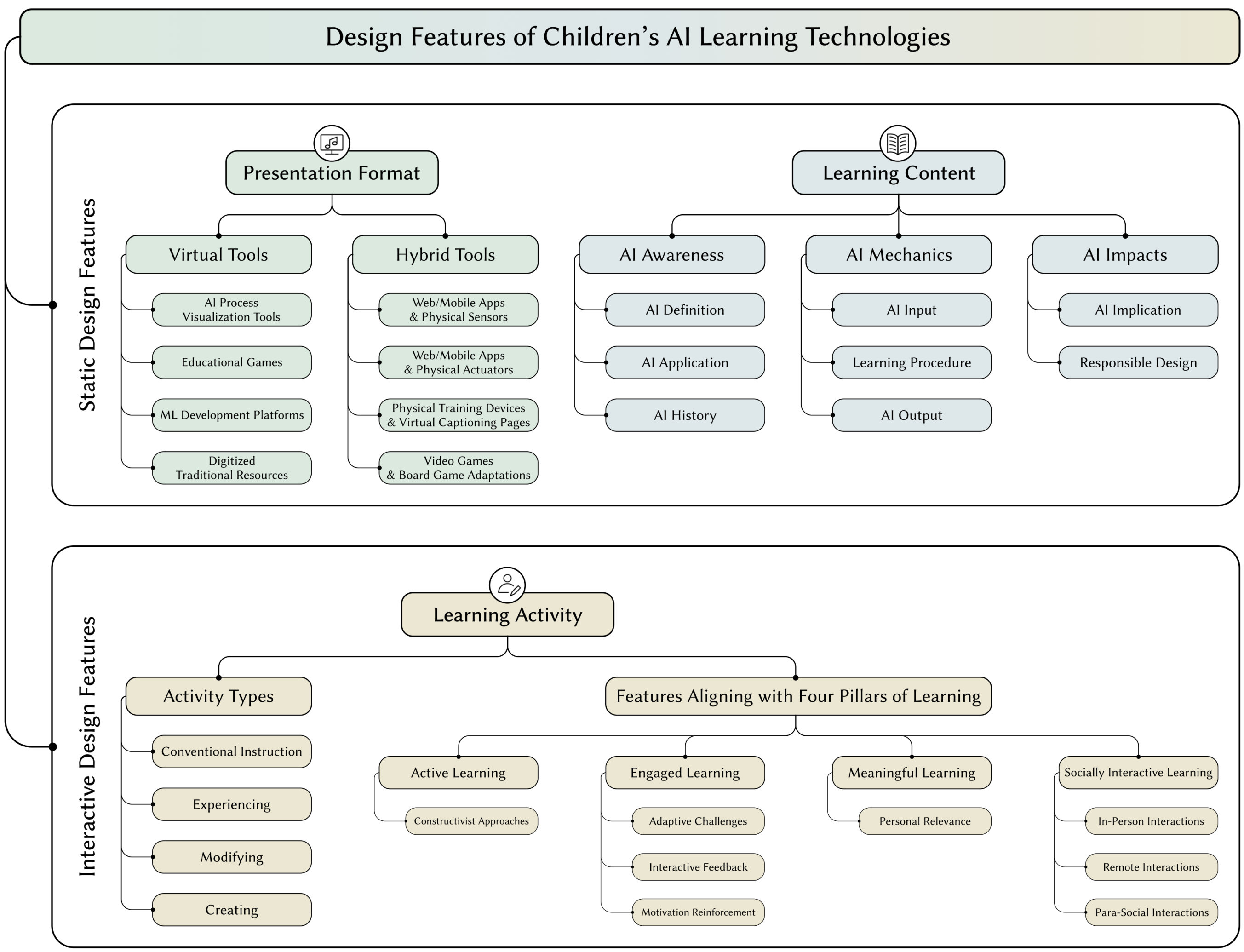
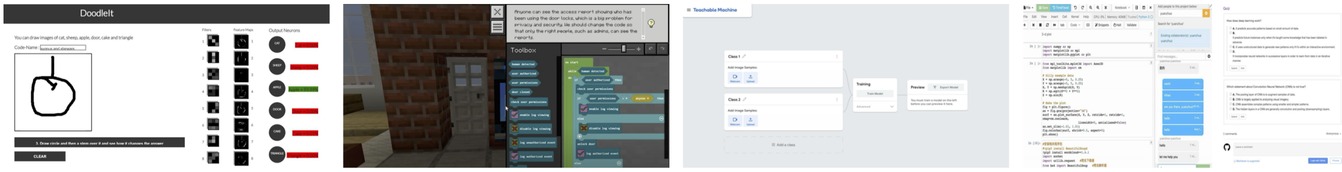


Figure 2: Taxonomy of the identified design features



(a) (b) (c) (d)

Figure 3: Four categories of virtual tools include: (a) *DoodleIt*, an AI process visualization tool that illustrates how a convolutional neural network classifies images [64, 98]; (b) *Hour of Code: Generation AI*, an educational game where players address privacy issues by revising back-end code [28]; (c) *Teachable Machine*, a non-coding ML development platform for creating custom classifiers [16, 62]; and (d) the *Mo* website, which provides digitized traditional resources like lectures and assessments [124].

4 Findings

Among the 64 analyzed tools, 58 specify their intended age groups, with six vaguely mentioning being designed for children [16, 31, 45, 55, 75, 135]. These tools span all five developmental stages, with most aimed at middle schools (ages 12–15, 63.8%) and upper primary grades (ages 9–12, 63.8%). There is less emphasis on high schools (ages 16–18, 43.1%) and lower primary school grades (ages 6–9, 39.7%), with the least emphasis on kindergartens (ages 6 and below, 3.4%). The next sections present our findings on the design features of current AI learning tools for children, categorized into static features (presentation format and learning content in Sections 4.1 and 4.2, respectively) and interactive features (learning activity in Section 4.3). Please see Figure 2 for an overview. Section 4.4 outlines the interconnections between these design features and target age groups as well as the assessment methods for the analyzed tools.

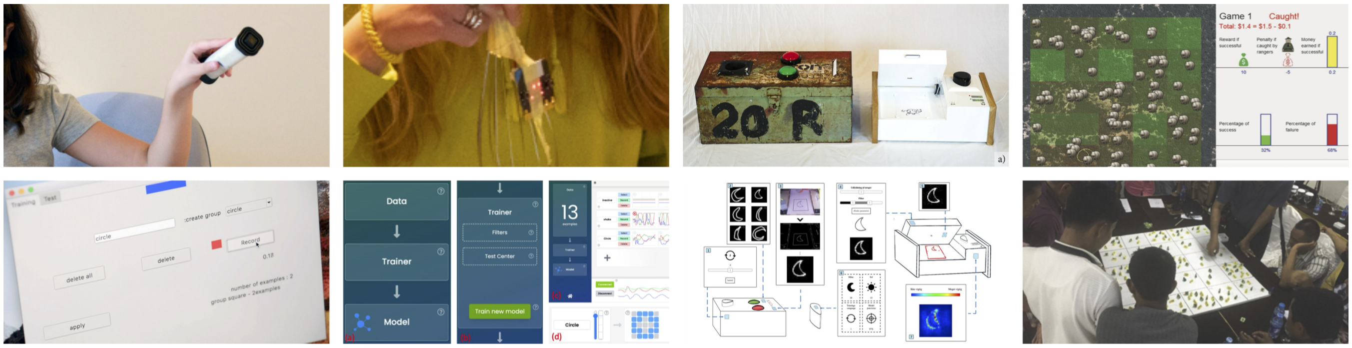
4.1 Presentation Format

Most analyzed AI learning tools are presented as virtual tools (75%), while the remaining are hybrid tools (25%). Notably, none of the included tools are entirely physical. Nonetheless, *Machine Learning Machine* included only physical components in its earlier version [52] but evolved into a hybrid tool in its most recent iteration [12]. Specifically, virtual tools can be further classified into four categories:

- **AI process visualization tools** are web apps featuring visually interactive elements (e.g., diagrams and charts) that demonstrate how AI functions. For instance, *DoodleIt* visualizes how a convolutional neural network recognizes sketches via multiple layers and feature maps [64, 98] (see Figure 3a). Other examples include image captioning systems that denote the image parts AI used for gender classification [72] and visual aids (e.g., pie charts, histograms, and word clouds) explaining ML processes in keyword extraction [53].
- **Educational games** integrate AI concepts into game mechanics and narratives. This category includes adventure games where learners tackle AI ethical issues in adventure scenarios [28] (see Figure 3b), action games promoting physical activities (e.g., guiding a chick across a busy street using postures captured on camera [102]), and puzzle games that challenge players to rotate multi-cube objects in latent space to match given shadows [61].
- **Machine learning development platforms** provide environments for designing, training, and deploying ML models. These include extensions for existing coding platforms, such as Scratch and MIT App Inventor, introducing new blocks for defining labels [135], collecting and labeling data [7, 48, 49], actuating outputs [84], and incorporating models into broader systems like Alexa [22, 23]. Additionally, there are new coding environments for children to develop AI projects, which either imitate existing coding platforms while introducing new blocks for model building (e.g., the "sensor" block to collect data [90]) or serve as companion systems for model deployment (e.g., a mobile app that children can customize by writing in Swift to export the models they created in a non-coding interface [112]). Lastly, there are non-coding model development platforms to design and train ML models. They consist of multiple visual interfaces for children to develop a custom ML workflow by dragging and dropping components that represent the main stages in the ML pipelines, typically covering data collection, labeling, and model testing [16, 62] (see Figure 3c).
- **Digitized traditional resources** are digital platforms enhancing conventional learning activities with interactivity. Examples include e-books containing AI lessons, quizzes, and integrated coding environments [134, 136] (see Figure 3d), as well as websites offering live-streamed AI lectures, assessments, and supplementary resources like codes and datasets [124].

In addition to these four types of virtual tools, we also identified four types of hybrid tools:

- **Web or mobile apps to train AI models using data collected from physical sensors**, such as *Scratch Nodes ML* [2, 42] (see Figure 4a) that provides a web interface for children to label their gestural data collected from a stick-like, physical device. Similarly, the mobile app *AlpacaML* [139–141], which allows children to train gestural classification model, uses micro:bits to capture acceleration data from their body parts.
- **Web or mobile apps to control physical actuators**: These tools link outcomes of ML models trained through virtual interfaces to physical devices. For instance, *ML-Machine* uses micro:bits to modify LED displays and activate motors based on results from web-trained ML models [14] (see Figure 4b).



(a) (b) (c) (d)

Figure 4: Four types of hybrid tools (physical parts at the top and virtual parts at the bottom): (a) *Scratch Nodes ML*, a web interface for training gesture classifiers with data from a stick-like device [2, 42]; (b) *ML-Machine*, a web app for training models to control micro:bits' LED displays attached to daily items [14]; (c) *Machine Learning Machine*, which uses two tangible boxes to train models on students' drawings and graphical web pages explaining model workflows [12]; and (d) a video game with tabletop adaptations enables learners to explore AI decision-making in gaming strategies [103].

- **Physical data labeling devices plus virtual captioning webs**, including web pages to explain underlying processes of ML models trained using tangible devices. For example, *Machine Learning Machine* features two physical boxes, one for labeling children's drawings and another for testing models with new drawings. The accompanying web pages, accessed through QR codes on the boxes, allow children to explore and modify the visualized ML process inside the boxes (see Figure 4c).
- **Video games with board game adaptations**, characterized by digital games paired with analog board versions. For instance, in Sintov et al.'s laptop game [103], students initially play against AI opponents on 2D grids to experience AI-enabled gaming strategies. The game is later adapted into a board game for two groups to compete on a physical map, where students simulate AI's decision-making observed in the virtual game (see Figure 4d).

4.2 Learning Content

The analyzed tools cover diverse AI learning content across three key areas: AI awareness, AI mechanics, and AI impacts. Table 2 summarizes the content within each area.

AI Awareness. More than half of the tools (68.8%) aim to build a conceptual understanding of AI through three topics: AI definition, AI application, and AI history. *AI definition* introduces the basic attributes of AI, including its ability to imitate human intelligence [136], its non-humanoid, programmable nature [28], and its difference from traditional computing systems [90]. For *AI application*, the tools explore AI's integration across six application areas: 1) art and creativity (e.g., AI-generated artwork and games [4, 102, 124]); 2) education (e.g., AI robots explaining algorithmic reasoning for children [121]); 3) environment (e.g., AI for natural resource management [25, 30, 82, 83]); 4) healthcare (e.g., AI in diabetes prediction and pandemic management [84, 124]); 5) service (e.g., conversational AI and individualized recommending systems [15, 55, 109, 138]); and 6) transportation (e.g., AI in intelligent vehicles and traffic management [1, 39, 55]). For *AI history*, the related content introduces the origin and key historical milestones of AI, such as the biography of John McCarthy [136].

AI Mechanics. All included tools (100%) address AI mechanics, teaching AI's technical rationales and the processes of developing ML models. It includes three sub-areas: AI input, learning procedure, and AI output. *AI input* focuses on data—the information AI uses to learn and make decisions—covering the concept of data

Table 2: Learning content of children's AI learning tools

Content Area	Definition	Sub Area	Explanation	Example
AI Awareness	Developing the basic understanding of AI	AI definition	AI's defining characteristics	[91, 134]
		AI application	AI use cases across industries	[22, 121]
		AI history	Origins and milestones of AI	[136]
AI Mechanics	Interpreting technical rationales behind AI	AI input	Impact and preparation of data in AI	[12, 18]
		Learning procedure	Underlying processes of ML models	[79, 119]
		AI output	Formats for manifesting ML outcomes	[9, 24]
AI Impacts	Engaging in AI in an informed, ethical way	AI implication	Benefaction and ethical issues of AI	[28, 72]
		Responsible design	How to design responsible AI systems	[1, 112]

[18, 119], discussing data diversity [111], and emphasizing the direct influences of data on AI [12]. It also addresses data collection methods, introducing common types of sensors and data for AI (e.g., visual [42, 102], audio [95–97], and physical [139]), as well as alternative data sources like public repositories (e.g., online news) [53, 117, 131] and private inputs (e.g., file uploading) [64, 91, 98]. Some tools further integrate the steps of data preparation for model training, including integration [25], analysis and cleansing [18], shuffling and splitting [51], and feature engineering [51].

Learning procedure concentrates on workflows of ML models, explaining basic concepts such as inferences [21], algorithms [1], and model-data-output relationship [12]. It also explores four predominant ML styles: supervised, unsupervised, semi-supervised, and reinforcement learning. Among the 54 tools that introduce these styles, most focus on supervised learning (81.5%), followed by unsupervised (13.0%), reinforcement (9.3%), and semi-supervised learning (3.7%). Tools typically explain these styles based on their defining concepts (e.g., supervision [79]) and working procedures of representative algorithms to support each style, including decision trees [117], k-means clustering [119], neural networks [4], and Q-learning [79]). Beyond ML styles, there is a focus on teaching how to build ML models, with most tools involving model training using block-based coding (50%) or workflow-based platforms without coding (46.3%), with fewer using text- (11.1%) or flow-based syntax (1.9%). These tools often incorporate a full ML training process, from basic tasks like data collection [111] and labeling [31] to advanced stages (e.g., algorithm selection [18] and parameter definition [90, 115]). They also explore model evaluation, explaining key concepts (e.g., accuracy and generality[12]), evaluation methods (e.g., cross-validation [124]), and outcomes of poor performance (e.g., over- and under-fitting [61]). Lastly, several tools cover strategies for enhancing model performance, such as data and parameter adjustments [79, 111] and optimization algorithms [89, 115].

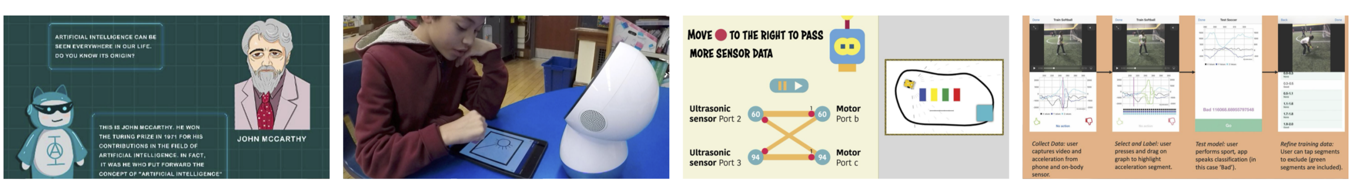
AI output examines how AI manifests its learning outcomes. Four main formats of AI outputs constitute the related content: 1) visual, such as on-screen indicators (e.g., green thumb-up for classification results of healthy foods [122, 123]) and LED lighting effects [2, 42]; 2) textual (e.g., classification results and evaluation metrics like confidence levels [72]); 3) audio, like sound effects and speech to convey ML outcomes [5, 139]; and 4) physical, characterized by robotic movements [22, 23, 45] and vibration [14].

AI Impacts. A limited number of tools (15.6%) introduce AI's societal and ethical impacts. On one hand, they highlight the double-sided nature of *AI implication*, discussing both its potential benefits for social welfare (e.g., enhancing mental well-being [121]) and AI-specific ethical concerns, which comprise the lack of fairness (e.g., discrimination by age [1], gender [72], and disability [28]), privacy and security (e.g., disclosing one's home address to the public [28]), and intended misuse of AI (e.g., harmful technology [1]). Some tools further delve into the root causes of these ethical dilemmas, such as dataset biases [12, 111, 112] and algorithmic biases [72]. On the other hand, the relevant tools seek to cultivate attitudes and behaviors required for *responsible design* of AI, promoting the creation of ethical AI systems by emphasizing the significance of inclusivity, transparency, and accountability while avoiding bias and harm [28, 112]. These tools also discuss practical skills for creating responsible AI, which highlight considering diverse stakeholder perspectives in dataset curation [1, 111, 112].

4.3 Learning Activity

4.3.1 Activity Types. We identified four types of learning activities in the analyzed tools, progressing from conventional instruction to experiencing, modifying, and creating. Note that some tools support multiple activities to provide auxiliary support to primary tasks. For instance, children can modify a completed tutorial AI project before creating an entirely new one [82, 83], and in such cases, we labeled the tools' activity based on their primary tasks, i.e., creating. These activity types include:

- **Learning through conventional instruction**, supported by very limited tools (6.3%), adopts traditional methods enhanced with interactive elements. This includes reading AI e-books [134, 136] (see Figure 5a), taking live stream AI lectures and asynchronous coding practices [124], and engaging with in-game AI lessons [94, 115].
- **Learning through experiencing**, the main activity of 10 tools (15.6%), engages children in exploring how AI works in specific application scenarios. It includes teaching AI concepts by involving children to directly play with AI applications, such as drawing with robots [5] (see Figure 5b) and enjoying AI-powered games, music, and toy cars [45, 102], and engage in problem-solving tasks (e.g., coding an agent to categorize flammable items [31]). Some tools also present children with ML working processes through interactive visualization and simulation. For example, the game *ML-Quest* tasks players to solve a maze by referring to previous routines, mimicking the supervised learning process through an immersive experience.



(a) (b) (c) (d)

Figure 5: Four learning activity types, including: (a) *AI World* that supports conventional instruction by guiding children to read an AI e-book [136]; (b) the robot *Jibo*, which enables learning through experiencing AI's applicability in collaborative drawing [5]; (c) *Neural Network Playground*, which promotes learning through modifying neural network weights [79]; and (d) *AlpacaML* allowing AI learning through creating custom gestural classifiers [139–141].

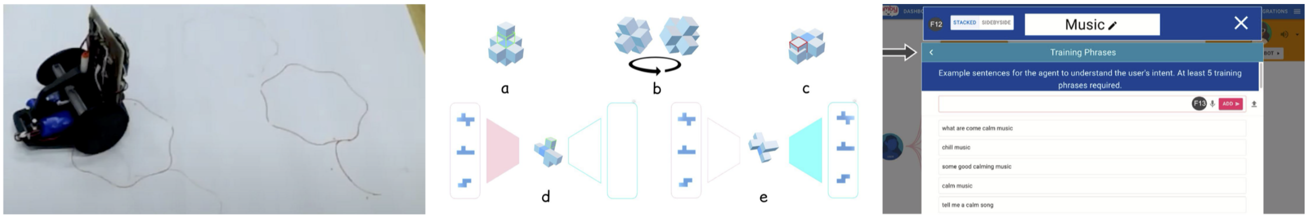


Figure 6: Design features potentially supporting active learning: (a) *Doodlebot* achieves exploratory learning by enabling children to explore AI-generated drawings [121]; (b) *Shadow Matching Game* allows problem-based learning by tasking children to match multi-cube objects to given shadows [61]; and (c) *AI Made By You* supports project-based learning by guiding children to create their conversational agents [109].

- **Learning through modifying** (20.3%) emphasizes hands-on experimentation with pre-trained AI models and applications. These tools support children in altering model parameters (e.g., changing data labeling rules [117, 131, 132] and modifying neural network weights [79]; see Figure 5c) and observe the subsequent outcomes. These activities also expand to revising codes (e.g., adding or deleting coding blocks of a completed project [28]) and switching model types (e.g., Naïve Bayes vs. Support Vector Machine [18]) to help children understand how this affects ML processes and outcomes.
- **Learning through creating**, the primary activity of most tools (57.8%), engages learners in defining their activity goals and creating AI projects from scratch. This includes a series of tasks to reflect different stages of ML model development (see Figure 5d), mainly starting with label curation (e.g., defining gesture types for recognition [139–141]) and data collection (e.g., building individual or shared datasets [55, 111, 112]). Then, such tools often involve children in training (e.g., labeling data and setting model specifications [16]) and testing their models (e.g., playing a game scoring by the model's confidence levels [111, 112]). Several tools also support model deployment for real-life applications, such as integrating a conversational AI into devices compatible with Google Assistant [109], uploading models into coding platforms (e.g., Scratch) to make games [139], and redesigning daily items with models (e.g., turning plush toys into interactive devices [113]).

4.3.2 Design Features Aligning with Four Pillars of Learning. Based on the definitions of the "four pillars of learning" [41], we found four sets of design features that may improve the effectiveness of children's AI learning activities.

Active Learning. The first design feature set may promote active learning through ***Constructivist Approaches***, which involve interactive manipulation and hands-on tasks to enable children to actively explore AI concepts. This feature is achieved by tools supporting three sub-classes of activities: exploratory, problem-based, and project-based learning. *Exploratory learning* describes those that grant children autonomy and flexibility to explore AI at their own pace, like freely tinkering with AI-themed e-books [134, 136], AI applications [121] (see Figure 6a), and visualized ML workflows [18, 64, 98]. By introducing certain levels of structure in learning activities, *problem-based learning* encourages students to address specific AI-related problems and acquire AI concepts in this active problem-solving process. For example, the *Shadow Matching Game* [61] (see Figure 6b) includes a clear game quest—rotating three multi-cube objects to match given shadows—leading children to discover the simulated working process of variational autoencoders. Lastly, tools featuring *project-based learning* include more structure in learning activities. They often navigate children through AI projects using pre-defined objectives and outcomes (e.g., providing a clear milestone and checkpoints as students progress in learning activities [95–97], focusing on creating and iterating on a custom AI model or application from project ideation to model deployment [109] (see Figure 6c).

Engaged Learning. The second group of design features—including adaptive challenges, interactive feedback, and motivation reinforcement—may help retain children's attention during learning activities and thus foster engaged AI learning. ***Adaptive Challenges*** focus on adapting learning activities to meet diverse learning needs, often using a "*low floor*" [93] for easy access. This is implemented by reducing the complexity of learning activities, such as concentrating on flow- and block-based coding activities to minimize syntax errors [85], avoiding exposure to sophisticated yet unnecessary materials (e.g., hiding detailed parameters of pre-trained ML models [24, 49] and including minimal text in AI learning activities to cater to young children's language ability [123] (see Figure 7a), and shortening learning tasks to match children's limited attention spans [117]. Some tools also offer instructional support by presenting children with starter projects [55], providing coding hints [28], and designing coding blocks with shapes and colors that suggest their functions yet hiding irrelevant options [82, 83]. In addition, several tools are designed using intuitive, minimalist interfaces to enhance visual clarity and reduce perceived complexity [21, 117], making learning experiences more approachable and engaging for diverse learners. On the other hand, the examined tools also tackle adaptive challenges with a "*high ceiling*" [93] to allow advanced exploration through leveled, flexible scaffolding, which is typically achieved by structuring learning activities from a basic to advanced level, e.g., establishing multi-level tasks increasing gradually in technical complexity [25–27, 29, 30]. Many tools also provide more experienced learners with a chance to delve into complex AI concepts, such as an advanced mode for changing parameters of models trained

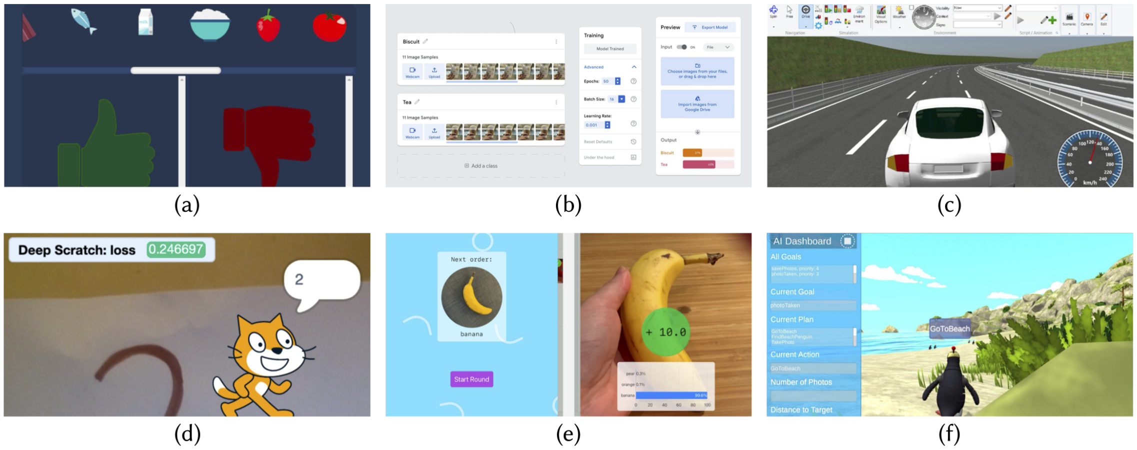


Figure 7: Design features potentially supporting engaged learning: (a) *PopBots* builds a low floor by simplifying learning activities with minimal texts [122, 123]; (b) *Teachable Machine*, which builds a high ceiling by offering advanced options for tweaking model parameters [16, 62]; (c) a virtual-reality car-driving platform that includes attention-capturing feedback [75], (d) *DeepScratch* providing cause-and-effect feedback by showing results based on input [7]; (e) a companion game for *Co-ML* to integrate reward mechanisms by scoring model confidence levels [111, 112]; and (f) *PRIMARYAI* that motivates children to explore AI applications in wildlife protection through a narrative [82, 83].

in basic modes [16, 62] (Figure 7b), coding blocks for exploring more sophisticated algorithms [21], and the "information button" to access extra learning content [117, 131, 132].

Another design feature for engaged learning is ***Interactive Feedback***, which further encompasses attention-capturing and cause-and-effect feedback. *Attention-capturing feedback* is typically designed with multi-modal elements, such as visual, audible, and tactile formats, to engage and retain children's focus on AI learning activities. Examples are appealing animations [102], game scenarios [89], and augmented or virtual reality environments [75, 136] (Figure 7c). On the other hand, *Cause-and-effect feedback* helps learners explore and manipulate AI concepts dynamically, which includes computers and robots' reactions to children's actions, e.g., instantly providing classification results when students input new data [7] (see Figure 7d) and robots moving in response to learners modifying model parameters [79].

Finally, ***Motivation Reinforcement*** potentially facilitates engaged learning using extrinsic motivators to enhance children's engagement and persistence in learning activities. This feature involves introducing *reward mechanism*, providing reinforcement when learners achieve goals aligned with AI learning objectives, e.g., awarding scores based on model accuracy [111] (see Figure 7e) and distributing in-game currency when students complete missions [1]. The other approach is establishing a *goal-oriented narrative* that motivates children to progress through AI learning activities by becoming invested in the narrative's outcomes. Such goals are often thought-provoking, such as missions to destinations like Europa [85] and future scenarios [1], and seek to promote social welfare, e.g., combating discrimination [1, 28] and protecting environment [25, 82, 83] (see Figure 7f).

Meaningful Learning. The third design feature set may foster meaningful AI learning with ***Personal Relevance***, which enhances the connection between AI learning experiences and children's funds of knowledge. These designs focus on creating *familiar contexts* by anchoring AI learning activities in children's personal

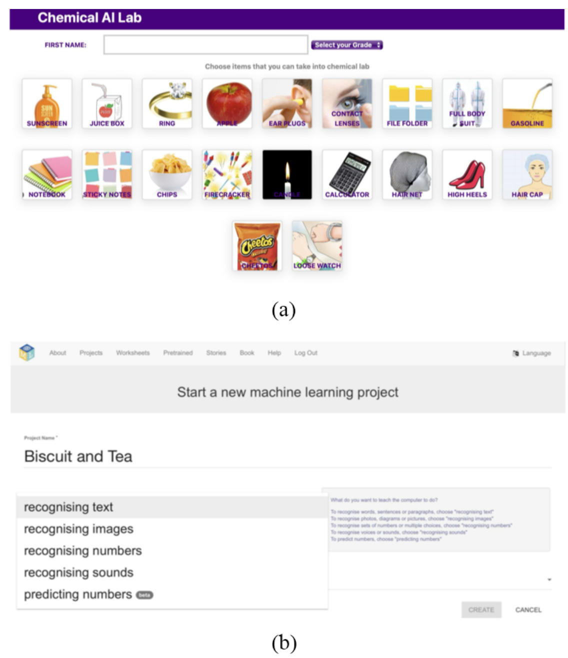


Figure 8: Design features potentially supporting meaningful learning: (a) *ChemAIstry* embedding AI learning activities into children's familiar context of school chemistry labs [67] and (b) *Machine Learning for Kids*, which enables students to train personally relevant ML models by supporting various types of input [55].

experiences. By embedding familiar items, daily contexts, and existing knowledge, these activities aim to make AI concepts more relatable, thereby enhancing students' understanding and retention. For example, some tools ground AI learning activities into common, real-life scenarios, e.g., playing a food recognition game mirroring family cooking experience [111] and labeling safe and unsafe items in school chemistry labs [67] (see Figure 8a). On the other hand, several tools foster personal relevance by constructing a "*wide wall*" [93], encouraging creative expression by enabling children to design and personalize elements in their own AI projects. For example, they can select avatars and voices for their conversational AI [109] and customize the appearances of their in-game AI agents [1, 117, 131, 132], which strengthen the perceived relevance of learning activities. Other tools also enable students to adapt AI projects to topics with personal significance to them, such as allowing them to define labels for classification model [9], collect personally meaningful data [112], and use various Scratch extensions [22, 23] and different model input and output types [55] (see Figure 8b) to create expressive projects.

Socially Interactive Learning. The fourth design feature set, which likely facilitates socially interactive AI learning, can be grouped based on the types of interactions supported by the tools: in-person, remote, and para-social interactions. The first feature can support ***In-Person Interactions***, namely, direct, face-to-face teamwork, by creating collaborative learning experiences and peer competition. *Collaborative learning* encourages exchange of knowledge between learners to deepen their understanding of learning content, achieved by organizing in-class discussions for students to explain AI concepts to one another (Figure 9a) and assigning complementary roles for children to collaborate on shared goals (e.g., one providing data while the other managing model training interfaces [2, 42]). Conversely, some tools motivate learners through *peer competition*, such as developing a dedicated shared interface for organizing in-class competitions, where students train models to achieve the highest prediction accuracy [51] (Figure 9b).

The second design feature for socially interactive learning concentrates on ***Remote Interactions***. On one hand, this is achieved through *synchronized collaboration*, which allows children to connect and collaborate with peers using online platforms and cloud services. For example, they can contribute to multi-user datasets stored and synchronized with CloudKit [111] (Figure 9c). On the other hand, some tools create *community-based learning networks*, which enable students to access AI learning resources by sharing, using, and building upon each other's work. These interactions include the exchange of datasets and models and project collaboration [124, 134] (Figure 9d).

The last design feature supports ***Para-Social Interactions*** between children and non-human or virtual characters, likely fostering AI learning activities by taking two roles. As *tutors*, the characters present and explain learning materials, such as the in-game non-player character introducing the concept of fairness to players [28] (see Figure 9e). As *companions*, they provide positive affirmations to encourage exploration of learning activities (e.g., an in-game agent saying, "You did well solving the problem!" [28]; see Figure 9f). Efforts are also made to strengthen children's emotional connections with non-human characters, such as designing a robot with expressive facial displays to enhance empathy and mental engagement [123].

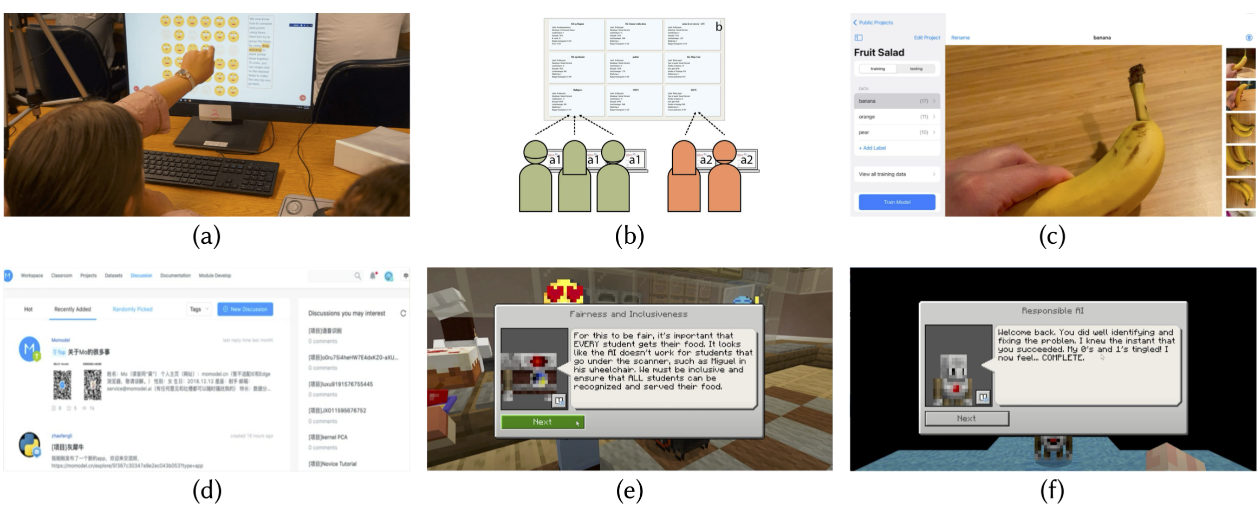


Figure 9: Design features potentially supporting socially interactive learning: (a) *SmileyCluster* can promote collaborative learning by engaging children in exploring the visualized process of *k*-means clustering in pairs [119]; (b) *VotestratesML* integrates a competition panel for students to compare model accuracy with each other [51]; (c) *Co-ML* supports remote, multi-user data collection with cloud services [111, 112]; (d) *Mo* builds a community-based network to share and use AI learning resources [124]; (e) *Hour of Code: Generation AI* involves a virtual character explaining AI impacts through conversations with children; and (f) offering positive affirmations to encourage students to navigate through learning activities [28].

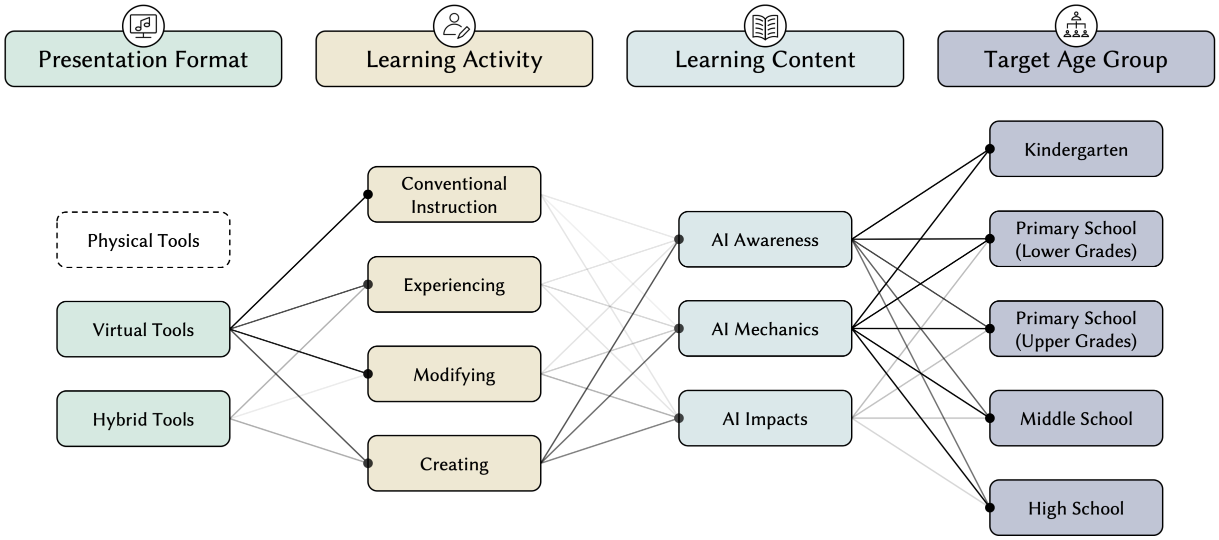


Figure 10: Interconnections among design features and target age groups. The line transparency shows the relationship strength based on the number of tools within each category. A more opaque line means a stronger connection.

4.4 Interconnection Overview of Design Features and Assessment Methods

Figure 10 illustrates the interrelationships among design features and target age groups. For the connection between presentation format and learning activity, virtual and hybrid tools support all four categories of learning activities, except for conventional instruction, which is solely supported by virtual tools and not by hybrid tools. This pattern is consistent across other learning activities—experiencing, modifying, and creating—which are primarily supported by virtual tools (70%, 92.3%, 67.6%, respectively), with hybrid tools offering less support (30%, 7.7%, 32.4%). Regarding the relationship between learning activity and content, all four AI learning activities are applied to teach all three areas of learning content. A clear trend also emerges, showing that all three content areas are predominantly taught by tools emphasizing learning through creating. Among tools covering AI awareness, most support creating activities (68.2%), followed by modifying (11.4%), experiencing (11.4%), and conventional instruction (9.1%). Similarly, tools for teaching AI mechanics focus mainly on creating (57.8%), with smaller proportions supporting modifying (20.3%), experiencing (15.6%), and conventional instruction (6.3%). For tools addressing AI impacts, the majority also prioritize creating (50%), followed by modifying (30%), experiencing (10%), and conventional instruction (10%).

Regarding the alignment of design features with target age groups, the analyzed tools address all three key areas across all ages, with AI mechanics consistently emphasized at every stage. AI awareness is particularly prominent in tools designed for younger children, appearing in 87.0% of tools for lower primary grades and 73.0% for upper primary grades, but it declines in middle school (62.2%) and high school (56%). Content on AI impacts is also more prevalent for younger groups, with 26.1% coverage in lower primary grades and 24.3% in upper primary grades, compared to 21.6% in middle school and 16% in high school. For learning activities, creating is the dominant activity for lower primary (65.2%), upper primary (62.2%), and middle school (62.2%) groups, but it is less prominent in high school (48%). Lastly, regarding presentation formats, virtual and hybrid tools are evenly distributed across the four age groups[2] without showing any clear age-related trends.

As for tool assessments, 46 tools (71.9%) were empirically evaluated based on participants' learning outcomes (e.g., understanding of AI topics [9]), learning experiences (e.g., attitudes [97], confidence [138], and motivation [79] toward AI learning), or tool usability (e.g., perceived satisfaction [7] and ease of use [89]). Learning outcomes were primarily measured through tests assessing students' AI knowledge after using the tools [102] and project evaluations that examined their ability to complete AI-related projects [139]. Learning experiences and tool usability were mainly assessed with self-reported questionnaires [117] and interviews to gather children's subjective feedback on their interactions with the tools [112], occasionally supplemented by observations that provided objective records of student engagement [43].

5 Discussion

AI stands as one of the most transformative technological advancements of both the present and likely the future, creating a pressing need to promote early AI education through the design of effective learning tools. Aligning with this need, we systematically surveyed existing AI learning technologies for children and analyzed their design features across three key dimensions: presentation format, learning content, and learning activity, providing a comprehensive overview of current design trends in children's AI learning tools. In this section, we discuss how our findings contribute to the existing knowledge on designing AI learning tools for children (Section 5.1). Building on this foundation, we further reflect on the gaps and

[2]With the significantly smaller number of tools for kindergartners, we excluded this stage from interconnection analysis due to insufficient representation.

share implications for future design and research in children's AI learning technologies (see Section 5.2).

5.1 Advancing the Current Understanding of Children's AI Learning Tool Design

In response to the growing importance of AI education, an increasing number of technologies have been developed to help children understand AI, resulting in 64 distinct tools examined in this study. These tools showcase a rich and diverse design landscape for children's AI learning, as reflected in their varied design features across the dimensions of presentation format, learning content, and learning activity (see Figure 2). Our findings contribute to the understanding of children's AI learning tool design in two key ways. First, through a systematic tool searching and filtering process, we captured a broader and more up-to-date range of AI learning tools compared to previous surveys, offering a more comprehensive perspective on their design features. For example, within the presentation format dimension, we identified two previously unexamined types of virtual tools (AI visualization tools and digitized traditional resources) and four new types of hybrid tools, extending prior surveys that only considered physical and virtual components separately (e.g., [77, 126]). For learning content, we proposed a novel three-dimensional framework to thoroughly outline learning materials across tools, covering previously overlooked topics such as AI awareness (e.g., AI's definition and history [66]), mechanics (e.g., AI input and output types [105, 106]), and impacts (e.g., creating responsible AI [38, 77]). Additionally, we organized a series of AI learning activities—ranging from conventional instruction to experiencing, modifying, and creating-based learning—along with four design feature sets that may enhance the effectiveness of these activities by aligning with the theoretical framework of the "four pillars of learning" [41], complementing existing reviews that only analyzed specific activity types (e.g., [11, 116]). Together, our findings provide a more comprehensive and current overview of design features in children's AI learning tools, highlighting their potential to ensure educational effectiveness and broadening the understanding of design trends in this emerging field for design and research.

Additionally, we developed structured taxonomies to systematically categorize the diverse design features of children's AI learning tools based on their core functionalities (Figure 2). Our taxonomies go beyond the enumeration found in existing works, which often list disparate design features without deeper integration. For instance, instead of treating distinct AI concepts (e.g., neural networks [66] and nearest-neighbor algorithms [77]) as isolated pieces of learning content, we grouped them under a broader theme called "learning procedure" within the category of AI mechanics. Similarly, rather than viewing "coding" as a standalone activity, as seen in earlier surveys [77], we included it in our higher-level category, "learning through creating," highlighting the essential role of coding in enabling children to develop AI projects. These novel taxonomies offer a more comprehensive understanding of the foundational principles guiding the current design of AI learning tools for children, moving beyond mere description to establish meaningful connections across tools. To this end, our findings provide a valuable reference for both educators and designers seeking to broaden and deepen their understanding of children's AI learning tool design. Specifically, our proposed taxonomies could help educators explore how specific AI learning content might be effectively conveyed through tools with particular presentation formats and learning activities, supporting the strategic planning of interventions tailored to various learning needs and educational contexts. For designers, the taxonomies offer a way to identify key features of existing AI learning tools and suggest potential objectives for future designs that aim to address the diverse needs of children and educators. However, the practical applicability and effectiveness of the taxonomies require further validation in future research. In summary, we offer a practical guide for leveraging existing AI educational resources and advancing future AI education through thoughtful and strategic learning tool design.

5.2 Gaps and Implications for Future Design and Research on Children's AI Learning Tools

Our findings also reveal significant gaps in the design of current AI learning tools for children, which may result in an overall quality that fails to fully meet their diverse learning needs. In this section, we discuss these gaps and offer recommendations for creating more engaging and effective tools in the future.

5.2.1 ***Lacking Physical Formats and the Associated Tangible Learning Experiences.*** A critical gap identified in the examined tools is the absence of physical kits ($N = 0$) and physical components, with 75% of current AI learning tools for children consisting solely of digital elements, making them overwhelmingly virtual. While virtual tools offer versatility and scalability, the lack of physical components raises concerns, particularly given the unique advantages of tangible learning experiences. Research on children's preferences for coding kits has shown that tangible experiences with physical tools can provide comfort and enjoyment during coding tasks, increasing engagement without relying solely on digital devices [100]. Additionally, physical tools often encourage greater parental involvement in children's AI learning, as these components are more visible in the home environment compared to virtual tools, which are confined to screen interactions [128]. In contrast, virtual tools frequently carry negative perceptions, such as parental concerns about excessive screen time [127] and its potential impact on socio-emotional development [69], which reduce parental support in helping children navigate new concepts [73]. This lack of physicality in tool formats represents a missed opportunity to address the needs of both children and parents. Therefore, future research and design efforts should ***prioritize exploring and leveraging the benefits of physical formats,*** such as robotic systems [108] and tactile kits [71], to better bridge technology with real-world interaction and enhance AI learning experiences and outcomes.

5.2.2 ***Overemphasis on Learning AI Mechanics.*** There is a disproportionate emphasis on teaching AI mechanics—particularly supervised learning (81.5%)—at the expense of other critical content areas (AI awareness and AI impacts). While teaching AI mechanics is important, this narrow focus on supervised learning overlooks the vast array of machine learning algorithms, potentially restricting children's holistic understanding of AI and their engagement with machine learning styles. Therefore, we encourage designers to ***extend learning content to include diverse machine learning paradigms***, such as workflows, application contexts, and algorithms relevant to unsupervised [119], semi-supervised [26, 29], and reinforcement learning [79], supporting children to develop a more comprehensive understanding of AI mechanisms, their capabilities and limitations, and ultimately enabling them to apply AI applications more effectively and critically in real-life contexts.

On the other hand, the limited emphasis on AI awareness and AI impacts hampers children's ability to comprehend and engage with AI as a socio-technical system—an important motivation for developing AI literacy among children. It is particularly concerning that none of the analyzed tools sufficiently address the responsible consumption of AI, such as guiding children on identifying scenarios where deploying AI technologies may be ethically or socially inappropriate (e.g., when privacy, intimacy, and safety are at stake). Such conceptual knowledge of AI not only scaffolds comprehension of the technical procedures but also allows children to critically interpret and assess AI's societal role and its broader implications. We advocate for future design efforts to ***expand the focus on conceptual AI knowledge, especially AI awareness and AI impacts,*** to prepare children of different age groups with a more thorough understanding of AI as a socio-technical system for navigating the challenges and opportunities of an AI-driven world. Lastly, given the recent prominence of GenAI, the learning content could be expanded to further include topics such as its fundamental mechanisms, capabilities, and various application scenarios.

5.2.3 ***Dominance of Classification-Focused Creative Activities.*** Our findings also highlight significant gaps in the design of tool-supported learning activities. Most of the examined tools focus on engaging children in creating custom AI projects, particularly classification models. This emphasis may stem from a focus on teaching AI mechanics, specifically supervised learning, which is predominantly used for classification tasks [101], along with a concentration on creating-based activities (59.4%). However, there are other types of activities that may warrant more diverse AI learning experiences. For instance, Kaspersen and colleagues [52] designed an unplugged card game to teach the ethical principles of AI design. In this game, students use data cards (describing data sources such as news and user locations), people cards (representing stakeholders like colleagues and siblings), and ethics cards (posing questions about ethical issues, such as privacy concerns) to reflect the potential impacts of a supervised learning system on various stakeholders. Resonating with this card game, we encourage designers to ***diversify AI learning activities in future AI learning technologies,*** thereby enhancing children's AI learning experiences with a broader range of activity options and more effectively addressing diverse individual preferences for learning activities. However, the current lack of empirical evidence leaves it unclear which learning activities are best suited for each age group, emphasizing the need for a more nuanced approach to age-appropriate tool design. Future research is needed to explore the suitability of technology-supported AI learning activities for different ages. Such research can help educators and designers select and develop tools that align with children's developmental characteristics, maximizing educational benefits at various stages.

5.2.4 ***Entry Barriers for Young and Novice Learners.*** Another design gap is that current AI learning tools are rarely intended for young children, which may stem from perceived requisites for technology-based AI learning, such as foundational math knowledge [33] and the ability to use technical devices [88]. However, children as young as 4 to 6 could grasp fundamental AI concepts, like the basic workflow of supervised learning [123]. As such, we see an opportunity for research and design initiatives to ***explore and broaden the potential for AI learning among young children***, to inform the creation of age-appropriate AI interventions and help young people establish AI literacy from an early age. Additionally, when designing new tools for young children, we suggest that designers ***consider target learners' prior coding skills.*** This recommendation emerges from our findings that over half of the examined tools require some level of expertise in block-based coding (50%) or text-based coding (11.1%), with only a few providing companion coding instructions [112, 139]. While coding can cultivate a mindset aligned with AI's systemic and analytical characteristics, it is not essential for understanding AI concepts and may pose additional challenges for young learners and novices [59]. Future AI learning tools can make coding an optional component of learning experiences or include preliminary tutorials before coding tasks to lower these entry barriers and enhance the inclusivity of AI education.

5.2.5 ***Insufficient Research on Children's AI Learning from a Design Perspective.*** Finally, we observe a significant gap in research on children's AI learning tools through a design lens: the lack of dedicated studies investigating design features that causally enhance students' AI learning outcomes. Using the theoretical framework of the "four pillars of learning" [41], we identified four clusters of design features that are likely to enhance the effectiveness of AI learning activities by aligning with children's effective learning patterns. However, despite their theoretical promise, these features have not been rigorously validated for their causal impacts on children's AI learning outcomes. We thus urge further research employing robust empirical evaluation methods to ***examine the causal relationships between the identified design features and children's AI learning outcomes***—insights that are essential for guiding the development of more effective tools in the future.

5.3 Limitations

The current study has several limitations. First, our analysis focused on AI learning tools referenced in research papers or by academic communities within AI-related fields. Our findings, therefore, may not exhaustively represent the entire design scope. Second, since over half of the examined tools are not publicly accessible, our analysis relied on descriptions from authors and developers rather than direct experience, which may cause an incomplete grasp of their design features. Third, while we summarized the assessment methods of the included tools, we did not examine their effectiveness due to the lack of standardized assessments, insufficient empirical evidence, and variability of effectiveness across learners and contexts. Fourth, our chosen analytical design framework is not the only available option, which may constrain the scope of the findings we can offer. Lastly, we concentrated on tools for children's learning of AI and did not address those for non-STEM subjects. Nonetheless, exploring learning tools in non-STEM fields is a promising future research direction.

6 Conclusion

This paper examines the design of existing technologies to support children's AI learning. By conducting a systematic search and analysis of these tools' design features across three key dimensions, we identify current trends and gaps in AI learning tools for young learners, along with opportunities and recommendations for designing more effective AI learning tools in the future. We aim for these insights to serve as a robust foundation for research and design practices, consequently enhancing AI education for future generations.

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Appendices

Table 3: List of Examined Children's AI Learning Tools. "Y" indicates tools that are publicly accessible. "N" indicates those that are not. "-" means the information not provided by the tool developers.

Presentation Format	Name	Learning Content	Learning Activity	Target Age Group	Public Availability	Source
Virtual tools	Adventure Alongside AI	AI awareness AI mechanics	Experiencing	Kindergarten Primary school (lower grades) Middle school	N	[102]
	AI Made By You	AI awareness AI mechanics	Creating	Middle school	N	[109]
	AI World	AI awareness AI mechanics	Conventional instruction	Primary school (lower grades upper grades)	N	[136]
	AI-1: Who Is That Ocelot?	AI awareness AI mechanics	Creating	Primary school (lower grades upper grades)	Y	[29]
	AI-2: Mapping Terrain	AI awareness AI mechanics	Creating	Primary school (lower grades upper grades)	Y	[25]
	AI-3: Sustainable Farming	AI awareness AI mechanics	Creating	Primary school (lower grades upper grades)	Y	[26]
	AI-4: Ocean Observations	AI awareness AI mechanics	Creating	Primary school (lower grades upper grades)	Y	[27]
	AI-5: Water quality	AI awareness AI mechanics	Creating	Primary school (lower grades upper grades) Middle school High school	Y	[30]
	ArtBot	AI awareness AI mechanics AI impacts	Modifying	Primary school (lower grades upper grades) Middle school High school	Y	[117, 131, 132]
	BlockWiSARD	AI awareness AI mechanics	Creating	Primary school (lower grades upper grades)	Y	[90]
	ChemAIstry	AI mechanics	Modifying	Primary school (lower grades upper grades) Middle school	Y	[67]
	Co-ML	AI mechanics AI impacts	Creating	Primary school (upper grades) Middle school High school	N	[111, 112]
	Cognimates	AI awareness AI mechanics	Creating	Primary school (lower grades upper grades) Middle school	Y	[22, 23]
	CONVO	AI awareness AI mechanics	Creating	Primary school (upper grades) Middle school	N	[138]
	DeepScratch	AI mechanics	Creating	Primary school (lower grades upper grades) Middle school High school	Y	[7]
	Digits Interpolation Notebook	AI mechanics	Modifying	Middle school High school	Y	[61]
	DoodleIt	AI mechanics	Experiencing	Middle school	Y	[64, 98]
	Hour of Code: AI for Good	AI awareness AI mechanics	Modifying	–	Y	[31]
	Hour of Code: Generation AI	AI awareness AI mechanics AI impacts	Modifying	Primary school (lower grades upper grades) Middle school High school	Y	[28]
	LearningML	AI awareness AI mechanics	Creating	Primary school (upper grades) Middle school	Y	[95–97]
	Let's Chance	AI awareness AI mechanics	Creating	Middle school High school	N	[21]
	Machine Learning for Kids	AI awareness AI mechanics	Creating	–	Y	[55]
	ML-Quest	AI mechanics	Experiencing	High school	Y	[89]
	Mo	AI awareness AI mechanics	Conventional instruction	Primary school (upper grades) Middle school High school	Y	[124]

Presentation Format	Name	Learning Content	Learning Activity	Target Age Group	Public Availability	Source
Virtual tools	Neural Network Playground	AI mechanics	Modifying	Primary school (upper grades) Middle school	Y	[79]
	NLP4All	AI mechanics	Modifying	High school	N	[44]
	NLP4Science	AI mechanics	Experiencing	Primary school (upper grades) Middle school	N	[53]
	PoseBlocks	AI awareness AI mechanics	Creating	Primary school (upper grades) Middle school	Y	[47]
	PRIMARYAI	AI awareness AI mechanics AI impacts	Creating	Primary school (lower grades upper grades)	N	[82, 83]
	Q-learning Playground	AI mechanics	Modifying	Primary school (upper grades) Middle school	Y	[79]
	Scratch-NB	AI mechanics	Creating	Middle school	N	[91]
	Shadow Matching Game	AI mechanics	Experiencing	Middle school High school	Y	[61]
	SmileyCluster	AI mechanics	Modifying	High school	N	[119]
	Teachable Machine	AI awareness AI mechanics	Creating	–	Y	[16, 62]
	Tooee	AI awareness AI mechanics	Creating	Primary school (lower grades upper grades)	N	[84]
	ViPER	AI awareness AI mechanics	Creating	Middle school	N	[85]
	VotestratesML	AI awareness AI mechanics	Creating	High school	N	[51]
	Zhorai	AI awareness AI mechanics AI impacts	Experiencing	Primary school (lower grades upper grades)	Y	[57]
	–	AI awareness AI mechanics	Experiencing	Primary school (upper grades) Middle school High school	N	[4]
	–	AI awareness AI mechanics	Modifying	High school	N	[18]
	–	AI awareness AI mechanics	Creating	Primary school (lower grades upper grades) Middle school High school	Y	[24, 48, 49]
	–	AI mechanics	Creating	High school	Y	[65, 110]
	–	AI mechanics AI impacts	Modifying	Primary school (upper grades) Middle school	Y	[72]
	–	AI awareness AI mechanics	Conventional instruction	High school	N	[94]
	–	AI awareness AI mechanics	Creating	Primary school (upper grades) Middle school High school	Y	[15]
	–	AI mechanics	Modifying	High school	N	[115]
	–	AI mechanics AI impacts	Conventional instruction	Primary school (upper grades) Middle school	N	[134]
	–	AI awareness AI mechanics	Creating	–	N	[135]
Hybrid tools	AIThaiGen	AI awareness AI mechanics	Creating	Middle school	Y	[9]
	AlpacaML	AI awareness AI mechanics	Creating	Primary school (lower grades upper grades) Middle school High school	Y	[139–141]
	Doodlebot	AI awareness AI mechanics AI impacts	Creating	Primary school (lower grades upper grades) Middle school	N	[121]
	Gest	AI mechanics	Creating	Primary school (upper grades) Middle school	N	[43]
	Jibo	AI awareness AI mechanics	Experiencing	Primary school (lower grades upper grades)	N	[5]

Presentation Format	Name	Learning Content	Learning Activity	Target Age Group	Public Availability	Source
Hybrid tools	KAI	AI mechanics	Creating	Primary school (upper grades) Middle school High school	Y	[108]
	Machine Learning Machine	AI mechanics AI impacts	Creating	Middle school High school	N	[12, 52]
	ML-Machine	AI awareness AI mechanics	Creating	Middle school	Y	[14]
	PlushPal	AI awareness AI mechanics	Creating	Primary school (lower grades upper grades) Middle school	Y	[113]
	PopBots	AI awareness AI mechanics	Modifying	Kindergarten Primary school (lower grades)	N	[5, 120, 122, 123]
	Solving Problems of Tomorrow	AI awareness AI mechanics AI impacts	Creating	Primary school (lower grades upper grades) Middle school	N	[1]
	Scratch Nodes ML	AI awareness AI mechanics	Creating	Primary school (upper grades) Middle school	N	[2, 42]
	–	AI awareness AI mechanics	Creating	High school	N	[39]
	–	AI mechanics	Experiencing	–	N	[45]
	–	AI awareness AI mechanics	Creating	–	N	[75]
	–	AI awareness AI mechanics	Experiencing	High school	N	[103]