Towards Hands-On Learning for Supporting AI Literacy Education Across Age

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Abstract

The rapid development of Artificial Intelligence (AI) in user-facing technologies is resulting in increased human-AI interaction in everyday life and may reshape the foundations of teaching and learning. At the same time, ethical and privacy concerns, as well as a lack of understanding of how these tools work can hinder the successful adoption in education contexts. In this paper, we argue that improving AI literacy cannot occur separately from the first-hand experience of interacting with AI-powered technology. We propose that understanding technical systems through hands-on activities can support AI literacy. We illustrate the idea of hands-on learning through two use cases: (i) social robots in primary and secondary education and (ii) Intelligent Tutoring Systems (ITS) in higher education. By building on tangible experiences, students might better understand AI principles and their practical relevance than when receiving solely theoretical materials.

Keywords

AI Education, Data Literacy, Intelligent Tutoring Systems, Social Robots, Human-AI Interaction

1. Introduction

The rapid development of Artificial Intelligence (AI) in user-facing technologies, such as social robots or intelligent tutoring systems (ITS), reflects the increasing integration of human-AI interaction into everyday life [1, 2]. According to UNESCO, the advancement in text- and speech-producing AI is likely to reshape the foundations of teaching and learning [3]. At the same time, previous research has shown that ethical and privacy concerns, as well as a lack of understanding of how these tools work, can hinder the successful adoption in education contexts [4, 5, 6, 7, 8, 9]. Similarly, students' understanding of how an educational tool works has been shown to increase its acceptance [10]. The growing gap between the state of AI and students' AI literacy calls for better learning experiences that enable all learners — including children and adults — to safely and effectively deploy AI technology, including and beyond generative AI [11, 12].

In this position paper, we propose that understanding technical systems and their societal implications through hands-on activities can support AI literacy more effectively than solely theoretical curricula. We argue that AI education is most effective when it is combined with the first-hand experience of interacting with an educational tool that suits the needs and level of the learner. We illustrate the idea of hands-on learning through two use cases targeting different student groups and using different forms of technology: (i) building social robots in primary and secondary education, and (ii) interacting with ITS in higher education[1]. This method enables practitioners to provide students with a deeper technical understanding of AI-powered technology and their societal and environmental implications.

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[1] We consider social robots and ITS forms of AI, consistent with a broad, established notion of AI[13]. This approach contrasts with recent trends in AI literacy assessments, which often focus exclusively on generative AI [14].

2. The State-of-the-Art of AI literacy education

In recent years, efforts to define and implement AI literacy in curricula across learning contexts have grown. Long and Magerko [15] were among the first to systematically synthesize the core competencies of AI literacy, which they define as "a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace". The authors derived 17 core competencies, including, among others, recognizing AI, data literacy, understanding action and reaction, ethics, and programmability. Additionally, the authors outlined design considerations, such as using embodied tools and promoting transparency, to help designers and educators create learner-centered AI.

Within the context of K-12 education, Touretzky and colleagues [12] introduced five *Big AI Ideas* that students should know: (i) Computers perceive the world using sensors; (ii) Agents maintain models/representations of the world and use them for reasoning; (iii) Computers can learn from data; (iv) Making agents interact comfortably with humans is a substantial challenge for AI developers; and (v) AI applications can impact society in both positive and negative ways. Similarly, in an exploratory review, Zhou and colleagues [11] assessed 49 existing AI learning tools and curricula for K-12 AI literacy. The authors identified major trends in K-12 AI literacy education, including: (i) structured series courses teaching basic Machine Learning concepts with existing AI education tools; (ii) short workshops using interactive data visualization and toy problems to teach basic algorithms; (iii) learning environments enabling students to develop basic AI applications with block-based programming; and (iv) accessible and engaging Graphical/Text-based/Voice User Interfaces, enabling students to train and test Machine Learning models. The task of defining AI literacy has also gained traction among policy-making institutions: The European Commission and OECD [16] are currently developing a K-12 AI Literacy framework, comprising 22 competencies across skills, attitudes, and knowledge.

In higher education institutions, AI literacy learning materials are primarily designed to address the field-specific professional requirements of students, rather than supporting a basic understanding of AI [17]. In this context, [18] introduced the term "AI readiness", which refers to the preparedness of students to use AI in their professional life. Additionally, many AI literacy courses focus on students' programming skills to support AI literacy (e.g., [19, 20]). This is reflected in a scoping review by [17], which found that more curricula prioritized technical knowledge (e.g., machine learning and programming) over the ethical and societal implications of AI (e.g., algorithmic bias or AI's 'black-box' problem). While technical skills are useful for understanding AI as a concept, a recent review of 22 AI literacy assessments highlights that consensus among authors indicates the societal impact of AI and AI ethics are equally important aspects of AI literacy [14]. Consequently, students should be equipped with skills in all three domains (i.e., technical skills, societal impacts, AI ethics), extending beyond mere programming to safely and effectively interact with AI systems.

Hands-on learning activities are beneficial across all ages [21, 22, 23, 24], an idea rooted in Piaget's constructivism [25] and Papert's constructionism ([26], for a review see [27]). Yet in Zhou and colleagues' review [11], fewer than ten works focusing on AI literacy education used *Embodied Interactions* and only six addressed *Natural Interaction.* These two concepts were identified as crucial to support AI literacy education by [15] and [12]. We propose that involving students in the construction of and interaction with technology is more effective for supporting the understanding of technical systems and their societal and ethical implications than using solely theoretical curricula, as we will illustrate in the following use cases.

3. Use case 1: Social robots for primary and secondary education

Research on social robots in education has received significant interest over the past two decades, with a variety of different roles and different robots studied [28, 29, 30, 31]. Prior work highlights the positive effects of social robots on children's affective and cognitive learning outcomes across various domains such as literacy, second-language learning, and engineering where robots have been deployed as teachers, tutors, and peers [32]. At the same time, robots are still rarely seen in classrooms, libraries, or homes. Reasons for this include (i) logistical and technical challenges associated with deploying autonomous, yet effective social robots [32, 33], (ii) purchase and deployment costs opposed to limited school budgets [9], (iii) a lack of long-term engagement partly due to missing adaptivity and customization of current systems [28, 34], and (iv) unrealistic expectations of stakeholders regarding robot capabilities [35, 9, 36, 37, 38]. Instead of deploying costly, complex, and ready-to-use social robots, we propose a hands-on approach that engages children in both constructing social robots and interacting with them. By including children in the building process of low complexity Do-it-Yourself (DIY) robot kits (such as the Blossom robot (**Figure 1**, [39]) or Ono robot [40]), teachers can foster children's AI literacy and equip them with the necessary knowledge to create AI artifacts that they would understand technically.

Other fields have long included children in the building process of robots, most prominently to teach children about computer science and robotics. For example, Pedersen and colleagues [41] developed a computer science course in which 10- to 12-year-old children build (non-social) LEGO and fabric robots to learn about hardware, programming, and physical/mechanical topics. Similarly, Jackson and colleagues [42] investigated children's engineering motivation and self-efficacy, following participation in a soft robotics curriculum unit, in which children build a gripper robot. Scaradozzi and colleagues [43] included even younger children and developed a robotics curricula for primary school children, as part of which children build their own LEGO robots. These examples showcase established applications of robot-building activities to support children's technical education, a foundation we will extend to AI literacy using social robots, as demonstrated in the following section.

3.1. Curriculum example

This section outlines an example of integrating hands-on AI literacy learning into an 8th grade (13-15y) Natural Sciences and Technology (NST) curriculum, using the social robot Blossom [39]. NST classes are interdisciplinary courses, focused on students' technical skills alongside natural sciences (e.g., physics, chemistry, biology) and as such well suited for interdisciplinary robot-building activities. The 6-weeks curriculum (**Figure 1**) is designed to include the foundational elements of AI literacy (i.e., technical understanding, societal implications, and AI ethics [14]), while additionally incorporating lessons on robot and AI sustainability.

Through Weeks 1-3, children actively engage in robot construction, fostering their understanding of hardware, sensors, and data collection modalities (e.g., microphones, cameras). To complement this technical understanding, Week 4 introduces block-based programming, and Week 5 focuses on Large Language Models (LLMs) and AI safety, specifically addressing data privacy and the broader societal implications of AI. This is crucial as social robots increasingly engage in natural and autonomous interactions, yet children are often unaware of what data are collected from them and how they are stored and used ([44]). Discussions during this Week can include data storage and handling decisions, such as local versus cloud-based solutions and their consequences for data ownership, thereby supporting children's safe and educated use of AI technology. Week 6 shifts to the deployment of robots, enabling children to explore and make different deployment decisions (e.g., robot placement, required infrastructure), and consider their environmental and societal implications through a virtual classroom activity.

This curriculum offers a valuable starting point for implementation, though it should be adapted to local AI literacy curricula and target groups. Positioning it within NST classes leverages teachers' existing technical skills to support robot-building activities while additional resources to facilitate lessons are already openly available (e.g., [16, 45]) and are expected to increase in quality and accessibility with broader adoption. Ultimately, this example curriculum illustrates how involving children in the building process of social robots provides opportunities for hands-on learning to support AI literacy, enabling children to design personalized social robots, and, consequently, laying the foundation for sustainable and effective long-term human–robot interaction.

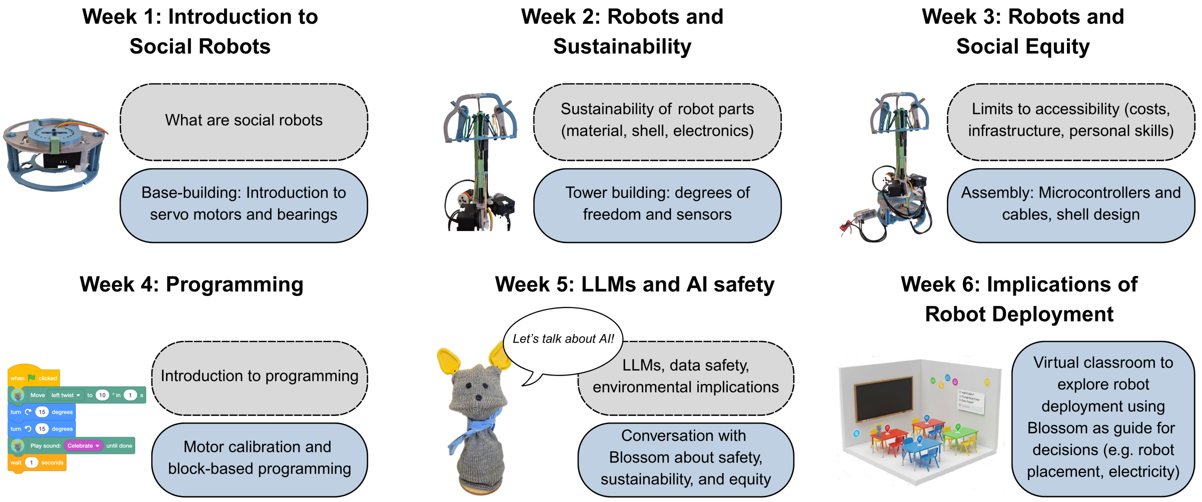

Figure 1: Structure of a 6-week (3 hours/week) NST curriculum, using the Blossom robot. Grey blocks indicate 45-minute theoretical lessons, while blue boxes represent 90-minute practical sessions.

4. Use case 2: Intelligent Tutoring System for higher education

ITS (i.e., AI artifacts designed to tutor students through scaffolding, targeted hints, and personalized feedback) have been proven successful in improving learning outcomes and student motivation across all ages, including higher education [46, 47]. However, when asked about potential concerns regarding the use of these tools, university students express high ethical expectations for educational tools [48, 49]. Their concerns range from social (e.g., reducing human interaction related to learning) to educational ones (e.g., potential unfair evaluation by professors after accessing student data) [50]. General privacy research indicates that concerns not only differ greatly between users but vary for the same user in different contexts [51], depending on their, often unconscious, stance regarding the tradeoff between privacy and functionality [52]. Addressing these varying concerns requires (i) flexible user settings for data collection and handling, tailored to individual preferences, (ii) transparency about available options to enable informed decision-making and foster increased AI literacy, thereby leading to (iii) a comprehensive understanding of the intelligent system and its available options, ensuring the provided information is comprehensible and actionable for users [53]. In short, students should be supported in actively controlling their data when interacting with an ITS, which will lead to improved AI literacy. In an educational context, fulfilling these requirements becomes additionally challenging due to power and information imbalances between teachers and students, as students are not necessarily able to assess a learning tool's benefits on their learning [54].

To address these requirements, two key solutions for an ITS can be defined as follows (**Figure 2**):

- **Controllability:** To adapt to students' varying data privacy needs, the tool should offer multiple personalization options that students can set with every use. These options are organized based on privacy invasiveness (no personalization, adaptation, full personalization), providing control without overwhelming the users. Moreover, this approach addresses the issue of power imbalance in education by using only pedagogically sound options that do not disadvantage privacy-conscious students.
- **Transparency:** Instead of a lengthy and complex privacy policy, students should receive direct, on-screen feedback while interacting with the tool about the privacy implications of their personalization choices, as illustrated in Figure 2. This ensures that students are fully aware of their decision's privacy implications and can adapt accordingly if necessary.

Extending the scope of an ITS beyond merely covering the learning content to transparently demonstrating its data handling could significantly improve students AI literacy. This approach enables students to better understand the types of data collected by these systems, their purposes, and benefits

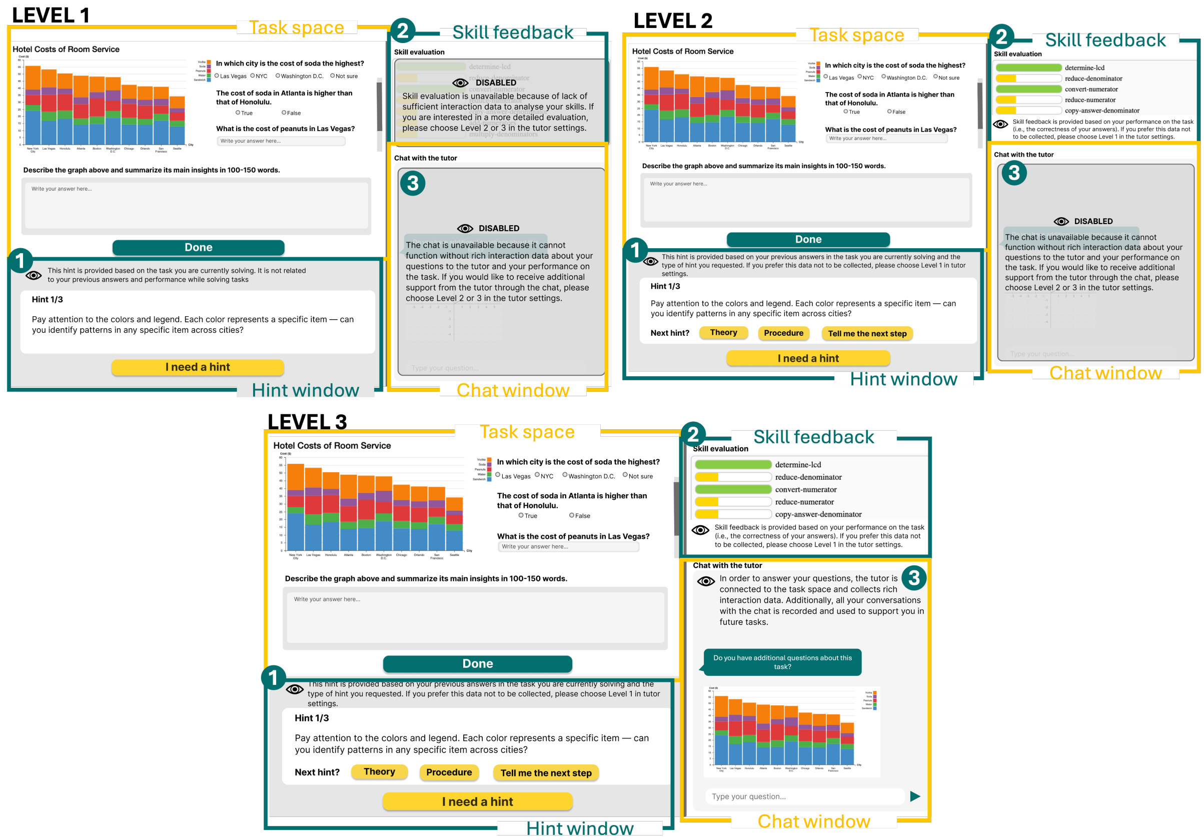

Figure 2: Draft screens, based on the interface of the CTAT tool [55], demonstrating proposed ITS features with varying personalization levels. The three screens demonstrate Level 1, Level 2, and Level 3 of personalization, which students can choose. Specific features would be enabled or adjusted based on the selected personalization level, as more data becomes available. Hint window (1): At Level 1, students passively receive general hints; at Level 2 and 3, they can request specific hint types. Skill feedback (2): This feature disabled at Level 1. At Level 2, it provided feedback based on answer correctness. At Level 3, it further incorporates click sequences and time spent on task. Chat window (3): Disabled at Levels 1 and 2. This window uses generative AI to provide additional support connected to student interactions in the task space at Level 3. The implications of choosing each personalization level are explained in dedicated information boxes (marked with an eye sign) to ensure informed decision-making.

and risks of providing these data. Such transparency would not only allow students to provide truly informed consent for the ITS — addressing a challenge unresolved by traditional consent form-based solutions [56, 57] — but also foster a deeper understanding of how such systems function. While we propose these controllability and transparency features for a specific tool, the same principles are applicable to other tutoring systems, whether commercial or open-source, given their common underlying mechanisms.

Therefore, our recommendation primarily targets developers of such tools to integrate transparent and educational data handling features into their existing systems. Transferring knowledge from this hands-on experience to broader contexts can be supported by an additional theoretical curriculum that builds on the insights provided by the ITS. Depending on the availability of resources in institutions, this curriculum could be implemented as an e-learning resource freely available in short modules to all students (currently the most common practice [17]) or offered in person by a relevant lecturer. In either scenario, we believe that more conscious interactions with intelligent tools can significantly support students in fostering their AI literacy, even in the absence of additional curricular resources.

5. Discussion

Emerging technologies, such as AI possess a great potential for creating personalized learning experiences at scale, for example for tutoring, content generation, and analytics [58, 59]. To benefit from this potential, students of all ages must be able to effectively use AI systems. In this position paper, we argue that improving AI literacy through hands-on learning activities can enhance students' learning outcomes more effectively than a theoretical curriculum alone, thereby making them more responsible and effective users and creators of AI artifacts. We illustrated this idea through two use cases: (i) building social robots in primary and secondary education, and (ii) interacting with ITS in higher education. Based on these two use cases, we identify the following benefits of implementing hands-on learning activities into AI literacy curricula:

Students gain first-hand experience with AI-systems, improving their technical understanding and providing insights into societal and ethical implications of AI. By engaging students in hands-on activities that encourage critical thinking about AI systems, our aim is to foster more conscious and safe interactions with these technologies. When students are given the opportunity to independently explore their educational tools, supported by appropriate guidance, they can develop into more responsible and informed users. The insights gained through these hands-on activities can then be reinforced through complementary theoretical sessions.

Teaching AI literacy as an integrated subject in other learning sessions. The proposed hands-on activities target not only AI and technical literacy but also other competencies, such as robotics, or learning new topics in general with a tutor. This enables their easier integration into existing curricula, requiring minimal additional instructional time. This is especially relevant because educators often have limited time resources and frequently cannot accommodate additional classes.

Students learn the most relevant aspects of AI through tools they use regularly. According to Faruqe et al. [60], the scope of AI literacy is not generalizable, as it depends on the frequency and intensity of AI use (i.e., those who interact less with AI also require lower AI literacy). Thus, by designing hands-on activities with age- and needs-appropriate tools, we ensure that students engage with aspects of AI literacy relevant to their experiences. For example, if an ITS is used in the classroom, understanding how it processes and uses data becomes an important learning objective. By applying the same design principles, we can also support diverse communities, including those in regions with limited resources or access to technology, by adapting the activities to suit available resources. In such contexts, students might benefit more from a different set of AI literacy skills compared to those in more technologically developed regions based on the systems they regularly interact with.

While the proposed approach offers a range of potential benefits, its practical implementation faces several barriers. First, limited (financial and technological) resources can prevent the use of AI technology, particularly in underdeveloped regions, thereby restricting access to AI literacy education. As discussed above, accessibility can be increased by adapting activities to suit available resources. For example, the concept of AIED Unplugged [61, 62] promotes adapting current AI-based learning tools to function without constant internet access or advanced hardware. Similarly, DIY robotic toolkits, such as the Blossom robot, can be built from a variety of accessible materials (e.g., wood, plastic) and use relatively inexpensive technical components (i.e., servo motors), reducing the total costs to approximately 100$. Second, the deployment of (generative) AI technology necessitates ethical guidelines and safety guardrails. The responsibility for these safety regulations lies with both technology designers and those responsible for deployment. As such, teachers and educators must be trained to evaluate and monitor safe human-AI interaction. As AI literacy curricula are being increasingly implemented globally these skills are crucial, regardless of the mode of education.

To conclude, while implementing hands-on AI literacy education faces practical and ethical barriers, its potential benefits are substantial. Such activities could enhance AI literacy education by providing students with age-appropriate, first-hand experiences with AI tools. Combining these practical experiences with theoretical curricula could support learning more effectively than current instructional methods, ultimately fostering a new generation of responsible, informed, and technical-literate AI users.

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Declaration on Generative AI

During the preparation of this work, the authors used X-GPT-4 to Grammar and spelling check. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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