Teaching AI to K-12 Learners: Lessons, Issues, and Guidance

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ABSTRACT

There is growing recognition of the need to teach artificial intelligence (AI) and machine learning (ML) at the school level. This push for AI/ML education at the K-12 level acknowledges the meteoric growth in the range and diversity of applications of ML in all industries and everyday consumer products, with Large Language Models (LLMs) being only the latest and most compelling example yet. Efforts to bring AI, especially ML education to school learners are being propelled by substantial industry interest, research efforts, as well as technological developments that make sophisticated ML tools readily available to learners of all ages. These early efforts span a variety of learning goals captured by the AI4K12 "big ideas" framework and employ a plurality of pedagogies. This paper provides a sense of the current state of the field, shares lessons learned from early K-12 AI education as well as CS education efforts that can be leveraged, highlights issues that must be addressed in designing for teaching AI in K-12, and provides guidance for future K-12 AI education efforts in order to tackle what to many feels like "the next new thing".

CCS CONCEPTS

• **Social and professional topics** → **K-12 education**.

KEYWORDS

K-12 AI education, K-12 CS education, machine learning

ACM Reference Format:
Shuchi Grover. 2024. Teaching AI to K-12 Learners: Lessons, Issues, and Guidance. In *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1 (SIGCSE 2024), March 20–23, 2024, Portland, OR, USA.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3626252.3630937

1 NEED & MOTIVATION

As the world gallops at an unprecedented pace toward increased automation with AI and its current, most popular avatar, ML, the conversation around AI education for school children is getting louder and harder to track. The rationale for teaching AI to K-12 learners appears to be a foregone conclusion; there can be little doubt that AI is currently the most powerful and transformative technology impacting our lives (for better or worse) in myriad different ways every day. It is believed that the ability to understand and use AI (or the lack thereof) will fuel the next digital divide in education [62]. Learning about AI is imperative.

The flurry of research, design, and development activity in AI education in these past years has been intense. While still useful, landscape papers on the state of the art of ML teaching and learning in K-12 from just three years ago (for example, [42]) already seem dated! Symposia and panels on this topic have been a must-attend agenda item at every recent education conference. Roughly five years into intense research and development in K-12 AI/ML education, this position paper helps make sense of these efforts. Its goal is to examine salient, recent literature, identify and highlight themes in research efforts, identify emerging tensions and challenges that must be tackled, and share perspectives and guidance on how to address them in future efforts. It also highlights worthwhile lessons from over two decades of K-12 CS education research that K-12 AI education will be well-advised to heed. Tedre et al.'s scoping review [59] bears some resemblance to this effort, however, it focuses on content and skills related to ML in K-12 along with pedagogical implications of teaching ML versus teaching CS.

What this paper is and focuses on. This paper is not meant to be an exhaustive literature review of research in K-12 AI education. Space limitations preclude it from being so, plus there already exist papers that have attempted systematic reviews of that nature (such as [50, 68]). As such, while the research cited represents the most salient lines of inquiry in the field, it does not constitute the universe of literature on K-12 AI education. Additionally, while AI education must include CS/AI technical education, AI ethics/societal issues (data integrity/agency/ethics), and uses of AI in service of learning CS, this paper focuses on the first aspect with the acknowledgment that technical learning of AI goes hand in hand with an understanding of AI ethics. However, the ***use*** of AI and LLMs in (CS or other) education is outside the purview of this paper. Also not covered are issues that fall in the realm of what is being called *AI Literacy*——the *non-technical* "knowledge, skills, and attitudes associated with how AI works, including its principles, concepts, and limitations, as well as how to use AI, such as its applications, implications, and ethical considerations" [57]——a literacy all students must develop (in various contexts and subjects) regardless of the technical learning of AI topics. It's reasonable to assume that given the complexity of AI technology development, AI education in early grades will naturally encompass more *AI literacy* elements than technicalities of AI, and the understanding of AI technology and the development of AI apps will be increasingly fostered in secondary grades.

Lastly, the paper is a crucial call to action to dovetail K-12 CS and AI education in deliberate ways that center learners, prepare teachers well, and make the teaching and learning of competencies in both fields (some overlapping and others distinct) inclusive, relevant, flexible, ethics-focused, and adaptive (to new developments).

SIGCSE 2024, March 20–23, 2024, Portland, OR, USA

ACM ISBN 979-8-4007-0423-9/24/03…$15.00
https://doi.org/10.1145/3626252.3630937

2 KEY THEMES FROM ONGOING, EARLY RESEARCH ON K-12 AI EDUCATION

This section outlines themes from several early efforts to study various issues related to teaching AI to K-12 learners. Curricula are being designed (as full-fledged courses, or curricular modules that can be integrated into CS or other subjects) for learners of all ages. These efforts target diverse grade bands and goals including:

- developing broad AI literacy (awareness about AI)
- developing understandings of AI/ML techniques such as decision trees, (un)supervised learning, neural networks, and generative adversarial networks (GANs) along with related issues of ethics, impacts, and careers
- ethics- and fairness-focused experiences
- examination of the appropriateness of diverse pedagogies (such a unplugged activities, creation of artifacts, project-based learning, embodied cognition) for developing an understanding about AI
- examination of pedagogies that serve one or more well-defined purpose(s), for example, broadening participation among women or youth belonging to specific groups,
- teaching AI basics from a CS topics lens,
- lifting the hood on how AI/ML works, or making AI less magical and more "explainable" (especially to older learners),
- integration of AI learning into/with other subjects,
- co-design with teachers and teacher preparation

The following subsections highlight salient themes from recent AI education research efforts at various levels of school education.

2.1 What learners should know & be able to do

The AI4K12 initiative published a set of guidelines for teaching AI at the K-12 level. The Five Big Ideas Framework [61] covers the spectrum of AI technologies in a tractable way (see Figure 1). These include–**Perception** (computers perceive the world using sensors.), **Representation and reasoning** (agents maintain representations of the world and use them for reasoning. Representation is one of the fundamental problems of intelligence, both natural and artificial), **Learning** (computers can learn from data. Many areas of AI have progressed significantly in recent years thanks to ML, a kind of statistical inference that finds patterns in data and the availability of large amounts of data to train ML models), **Natural interaction** (intelligent agents require many kinds of knowledge to interact naturally with humans, such as the ability to converse in human languages, recognize facial expressions and emotions, and draw upon knowledge of culture and social conventions to infer intentions from observed behavior), and **Societal impact** (AI can impact society in both positive and negative ways. Biases in the data, and in training algorithms used to train an AI system can lead to some people being less well served than others). AI4K12's Grade Band Progression Charts for each of the Big Ideas have catalyzed the creation of curricula and integration of AI activities by enthusiastic "early adopter" teachers. However, the emergence of a parallel set of goals and progressions outside of CS (with little-to-no connective tissue tying them to core CS concepts) raises concerns.

Ethics and critical examination of AI. A commendable aspect of early K-12 AI education efforts has been centering issues of ethics and bias in AI with learners of all ages. This acknowledges

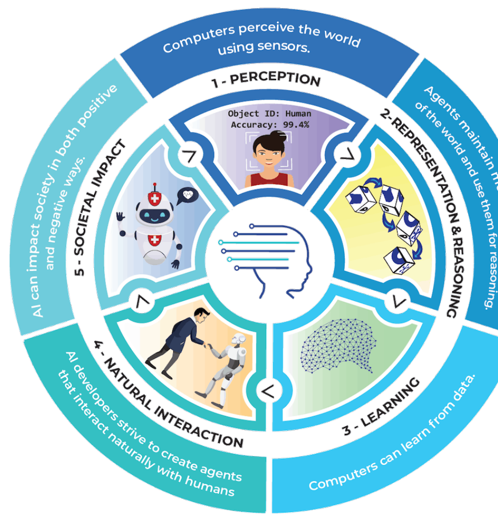

Figure 1: The Five Big Ideas in AI4K12.

the reality that while ML tools are exciting and have several uses for improving human productivity and benefiting human decision-making, they also harm users, especially those from historically marginalized communities [9]. In the 'CSFrontiers' AI & ML curriculum module (https://csfrontiers.org/ai-and-machine-learning.html) high school girls engage in socially-relevant AI experiences that include discussion of biases and ethics, and include critical examination of popular AI apps such as Quick, Draw! [2] and of the social impacts of AI on the environment and the criminal justice system. The MIT RAISE group (raise.mit.edu) has developed multiple middle school curricular sequences and resources— *DAILy*, *Creative AI*, *Dancing with AI*, and *How to Train Your Robot*, all of which embed AI ethics and critical examination of AI in addition to project-based engagement with ML techniques and tools [38, 66].

Data Agency & new CT skills A key breakthrough in K-12 CS and coding education was the recognition that computational thinking (CT) [25] comprises problem-solving approaches that transcend programming environments. Over time, conceptualizations of CT have expanded to include situated and critical framings [30]. While these skills are still necessary for the development of AI apps in traditional general-purpose programming environments, ML—which is now a central piece of AI (and AI education)—involves the use of data rather than code to shape AI applications. Additionally, there are calls for students to be taught data *agency* [58] in addition to data *literacy* to emphasize people's ability to not only understand data but also to actively control and manipulate information flows and to use them wisely and ethically. This emphasis on data and probabilistic models, and de-emphasis on algorithmic thinking, signals the emergence of a 'CT for AI' that is data-driven rather than the rule-driven CT of old [64]. (Somewhat related, CS education itself is changing in the age of LLM-assisted learning of programming with tools such as ChatGPT and Github Copilot that emphasize some introductory programming and CT skills such as problem-decomposition and code-reading over others [48]).

2.2 Pedagogies & instructional approaches

The research efforts underway in K-12 AIEd showcase a rich plurality of instructional strategies being employed to introduce learners of all ages to these new, fast-moving technologies. Pedagogies for teaching ML (specifically) cover the gamut from demonstrating how machines learn through playful unplugged activities for young students (e.g., [52, 67]) and using pre-designed models and tools for exploring ML, such as Google's *Teachable Machine*, with middle schoolers[38], games that help build intuitions about how ML techniques work (see below), interactions with, and lo-fi prototyping of, AI agents [15], having students become co-designers of their ML applications [64], using web-based AI APIs that can be used for classification in block-or text-based programming [35], engaging youth in critical, constructionist sense-making activities [43], and engaging high school girls in socially-relevant AI experiences involving classification of sentiment in online exchanges and examinination the ethics of Google's *Quick, Draw!* and biases in the criminal justice system [2], to integrating movement practices from dance in CS & AI learning in order to create culturally sustaining experiences where learners draw upon cultural ways of knowing as they explore identity across individual, social, and political dimensions [11].

Many AI education pedagogical approaches involve unplugged and hands-on "manual" engagement with the complex ideas undergirding ML and training of models as entry points to help students build intuitions about how these models work without engaging in coding or the mathematical complexity of ML concepts. Most of these experiences are also grounded in real-world applications and everyday experiences that help learners engage in a critical examination of societal issues of ethics, justice, and bias.

While a majority of current K-12 AI curricula rely on pre-trained models and APIs to demonstrate ML, some programming-focused curricular activities that leverage block-based programming environments take steps toward uncovering ML black-boxes [26, 29, 31, 32]. Recognizing that high school students may want to engage with actual code for training a model, albeit at different levels based on interest and ability, Broll & Grover [6] provide multiple levels of engagement and options to teachers and students for how deep they could go with high school students in unpacking gradient descent, training a decision tree, and coding a discriminator and generator in generative adversarial examples. They employ "levels of abstraction" [12] as a scaffolding tool– first introducing the basic algorithm in pseudocode, then providing "subgoal"-inspired [44] design blocks for implementing the algorithm and Parson's problems [46] for code completion that has been shown to scaffold programming in introductory CS courses. At the lowest level, they provide the entire code that implements the model. These levels introduce students to the entire lifecycle of designing an ML model and provide teachers with options to help learners engage at varying levels, while still ensuring that all students leave with an intuition of how the ML technique works [5].

2.3 Designed activities & free interactive tools

Several well-designed tools and environments have been designed and empirically studied in the last 5 years. Leveraging the familiarity of young learners with ubiquitous AI-based conversational apps such as Siri, Alexa and Google Assistant, a team at the University of Florida developed a novel development environment, AMBY–"AI Made By You"–for youth to create their own conversational agents. AMBY was iteratively designed with and for youth aged 12-13 to foster AI learning with features that enable users to generate training datasets and visualize conversational flow [33, 55, 60].

Some research efforts have focused on designing tools that lift the hood on how ML models actually "learn". In the *Contour to Classification* game, students work together as a neural network to classify images of animals, where the neural network has an input layer, two hidden layers, and an output layer [37]. The game supports student learning by providing the image classification experience using purely visual inputs to each layer. In *Find the Minimum Game* (Fig 2), students build an intuition of gradient descent [49], an algorithm often used in neural networks, by exploring the idea of learning through optimization, or minimizing error. Students embody an optimizer and try to find the minimum of an unknown/invisible function/graph [5].

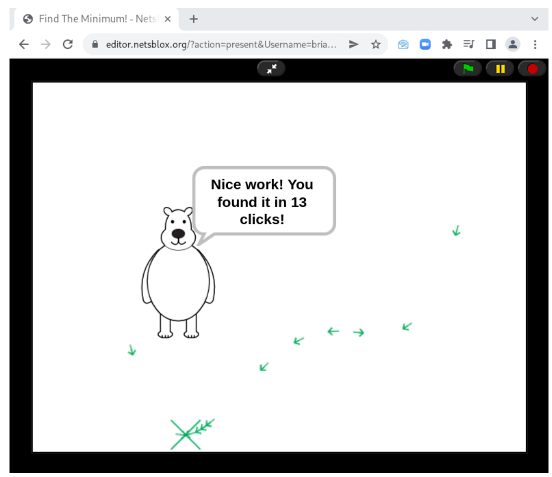

Figure 2: "Find the Minimum" game helps develop preliminary intuition of how gradient descent works [5]

Several freely publicly available tools are in wide use in K-12 AI education. Popular among these include GenAI's *Teachable Machine* [47], Google's *Quick, Draw!*, *Tensorflow Playground*, and *GAN Lab*, and ML4Kids [35]. Several tools extend existing block-based programming environments with AI blocks, or mechanisms to call AI-related APIs (for example, Cognimates, Craft2Learn, NetsBlox [4, 7]). AI4k12.org maintains a growing list of all these resources.

2.4 Integration of AI with other subjects

Several efforts underway are examining how to integrate AI into other subjects at various grade levels. At the elementary and middle levels, problems in science are leveraged as entry points for AI learning [14, 19, 45]. Activities have been designed for integration based on the Big 5 Ideas [52]. Wang et al. [65] describe curricular examples of secondary students creating AI-powered apps in science classrooms, such as a weather forecast module and a molecular biology AI module for studying the flow of genetic information, and for social studies classrooms (such as an AI module for analyzing Supreme court opinions). Alvarez et al. [2] share activities using real-world datasets along with AI and NLP Web APIs in NetsBlox, an extension of the Snap*!* [54] block-based programming environment, that could be integrated into high school social studies and science curricula. These include building a bot classifier and an app for analyzing sentiment (such as hate speech) in social media posts, lyrics, or chat conversations. The 'AI & Cybersecurity for Teens' (ACT) suite of curricular activities [[1]] introduces AI/ML in the context of cybersecurity. The research examined preparing high school teachers to integrate AI in their cybersecurity curricula [22].

2.5 Curricular co-design processes & teacher preparation

Curricular co-design with teachers is a mutually beneficial activity for both the designer/researcher as well as the teacher. When the subject matter is new to teachers, co-design is increasingly seen as a model for teacher PD as well [23, 53]. Co-design and participatory design with teachers appears to be a popular mechanism for the design of AI curricula for various grade levels in many research-based and other efforts (e.g., [18, 41, 45]). ML4STEM, a PD program designed for teaching ML concepts to STEM teachers [56] demonstrates the– (1) value of learning by design and collaborative participation, (2) effectiveness of hands-on learning with ML tools, (3) necessity of extended learning time for teachers, (4) the need for diverse examples of ML-empowered learning activities for various subjects and grade levels, and (5) the need for diverse teacher contexts such as subject and grade level. Other teacher preparation efforts [2] have involved using the teacher-learner-observer (TLO) model [20] to have teachers assist in learning, co-design, and critique of a draft curriculum followed by refinements and teaching (to students) following the PD. Lee & Perret [39] leveraged the middle school *DAILy* curriculum [38] to prepare high school teachers to integrate data science and AI into a wide range of STEM subjects in middle and high school.

2.6 A plethora of free curricular resources.

The many early efforts by researchers, early adopter teachers, education organizations (such as Code.org), and industry to design curricula and examine pedagogies to introduce AI/ML to K-12 learners have resulted in an ocean of open-access resources. There now exist several lists and repositories of such resources, the most comprehensive amongst these being maintained by AI4K12.org. The pace of growth in K-12 AI education literature and curricular/tool development is almost as hard to keep up as the exceptionally rapid advances in AI itself. Any publication attempting to present an overview of available curricula as in Druga, et al.'s 2022 paper [16] is soon outdated. A key lesson is that anything besides a "living" repository of such efforts is likely to be a futile effort.

3 CHALLENGES & TENSIONS IN TACKLING "THE NEXT NEW THING"

This section highlights the several issues that pose challenges to the task of educating students about AI or are tensions that push the boundaries of our current knowledge and understanding.

Rapidly Changing Landscape. AI/ML is a young field of study advancing at a dizzyingly fast pace. For many, the AI education "imperative" is barreling down the pike at a pace that makes it too challenging for teachers and other key stakeholders to keep up. K-12 CS Education has just about started to make noteworthy inroads with just over half of public high schools in the US offering foundational CS, and 7 states making CS a requirement for high school graduation. Against this backdrop, the exceptionally rapid pace of new developments in AI/ML makes accommodating it in CS curricula a challenge. Take, for example, the momentous arrival of LLMs in December 2022. Neither the AI4K12 framework nor the many early curricular research efforts made a mention of what is now the most exciting and popular example of AI for students. Additionally, there are still ongoing debates about the true potential—and potential harms—that AI represents in the near and long-term future. The relationship between humans and AI is still evolving and promises to be in a state of flux for some time. For example, when are humans creators of AI, and when are they correctors of AI, or are they simply data for AI systems? The shifting landscape makes it challenging to address these multiple new AI-related needs.

A Crowded Curriculum & AI's curricular relationship to CS, coding, and other subjects. Most AI learning is currently being conducted in CS classrooms. However, with its own learning goals and progressions, a key tension is how the additional content should be taught in the already crowded school curriculum. A related, but even more fundamental, question is how AI should be viewed vis-a-vis CS education. Is AI a subject with its own set of progressions and learning goals, or is it a part of (evolving) CS frameworks and standards? Should AI be taught as part of K-12 CS or separately? Which competencies overlap and which are distinct to CS and AI? Also pertinent is a re-look at the rationale, role, and goals of teaching coding. Should learners still learn to code? Teaching CS, coding, and CT in K-12 has been more about developing problem-solving skills. Teaching coding has been a vehicle to achieve that goal in addition to demystifying computing for *all students* and providing them with motivating experiences to be creators rather than mere consumers of software. This remains true even though the goals and pedagogies for teaching coding will need to adapt to the growing capabilities of LLMs to generate code. Additionally, since AI integration with other core subjects is also crucial, will it supplant the integration of (other) CS? Should integration with AI take precedence over non-AI CS integration? Should AI be the Trojan horse to aid CS integration? Regardless, it will be unwise to assume (or suggest) that AI replaces CS education.

Building Teacher Capacity. A paramount concern for K-12 AI education, as has been the case for K-12 CS education, is effective teacher preparation to teach AI. There is pressure on teachers not only to teach *with* AI (by incorporating LLMs, for example, in thoughtful ways), but also incorporate AI teaching and discussions of ethics across the subjects. This puts a strain not only on CS teachers, many of whom are tasked with teaching AI, but other teachers as well. For CS teachers, there is also the challenge of ***adjusting to the paradigm shift in learning goals and approaches pertinent to K-12 CS***. Novice CS teachers who have recently developed skills to teach CT for CS more broadly [25], may now need to adjust to approaches that de-emphasize algorithmic thinking to more data-driven approaches, as outlined in section 2.1.

How deep can/should activities go into AI/ML code and implementation? A key challenge of AI education in K-12 is that it has hitherto been seen as an advanced topic in CS, and as such has been offered as a course only as an advanced elective at the college level, or as a subject of in-depth study at the graduate level. Making fundamental AI concepts accessible without requiring mastery of the underlying mathematical concepts can be a challenge. Research on appropriate strategies and pedagogies for teaching ML, especially to K-12 students is still evolving with little clarity on how—and at what depth— to teach these complex ideas to younger learners [17, 27]. Evidence of Bruner's valuable perspective that "any subject can be taught effectively in some intellectually honest form to any child at any stage of development" [8] has been demonstrated in past research–children can grasp a surprising level of complexity when content is presented to them in ways that are developmentally appropriate [34]. In the context of AI, studies have demonstrated that children as young as 10-13 years of age can understand key ideas of ML classification (specifically data labeling and evaluation) through appropriately designed experiences with pre-trained models [27]. The are several arguments for going deeper and lifting the hood [6] on ML concepts–merely interacting with AI agents and ML models does not expose students to the underlying processes of ML [27], uncovering "black-boxed processes" will help students build appropriate mental models of ML [5, 27, 59], and deeper understanding will aid a more meaningful interrogation of critical issues such as ethics and bias in AI/ML [5].

AI Misperceptions in the Broader Discourse. Perceptions and beliefs impact people's judgments and their cognitive, motivational, and decision-making processes, thus influencing actions (such as choosing to pursue a certain major or career) [3]. For these reasons, children must build accurate perceptions and beliefs about a discipline and its associated careers. In the case of AI, we need to thread the needle between generating interest among students even as we make them aware of the many harms AI causes today and is projected to cause in the future. Furthermore, there is a tendency to make AI seem either magical, sentient, infallible, or overly human-like with an over-emphasis on anthropomorphizing AI in the way AI is spoken about or through humanoid representations. These misrepresentations contribute to the challenges of educating the next generation about AI. Since such (mis)representations are rife in mainstream discourse, K-12 education needs to work extra hard to address this challenge through approaches to demystify AI, lift the hood (to the extent possible) on how it works (and why LLMs, for example, are not always right and cannot become sentient) and presenting compelling examples of how AI is distinct from humans and can never possess all human capabilities.

Lacking an Evidence Base. For many of us involved in K-12 CS education, the arrival of AI education feels like too much too soon. Even as we are working on the many unresolved research questions about equitable CS for all learners and integrating it with data science and other subjects, there is now a need to address AI as well and do so deliberately and equitably. There needs to be more clarity if, when, and how to teach complex AI and ML ideas to K-12 learners as well as an understanding of cross-cutting competencies that can be leveraged across proximal STEM disciplines. There is also a need to to assess incoming knowledge and attitudes of K-12 students about AI, to be able to address misperceptions and contextualize learning experiences [36]. Lastly, we need research to support understanding how to integrate AI into other core subjects.

Clarifying Terminology. The distinction between broad (non-technical) AI ***literacy*** and learning technical AI concepts should be understood and clarified in curriculum design, teaching, and learning. Terminology matters, as we have seen in the need to clarify early on the difference between *digital literacy* and *CS education* for educators, administrators, and policy-makers. Research efforts thus far have blurred the lines, and programs engaging in teaching technical AI concepts are also sometimes termed *AI literacy*. 'AI education" especially in relation to K-12 CS education (as in this paper), is about literacy ***in addition to*** enabling learners to understand AI, create AI applications, use AI APIs and pre-trained models, or train an LLM, for example, to perform the kind of tasks AI-powered apps in the real-world do. AI education in K-12 is a progression toward increasing sophistication in the ability to understand and *create* AI. Using "AI Literacy" and "AI education" interchangeably (as in [65]) tends to fuel confusion.

4 TAKEAWAYS & GUIDANCE

4.1 Lessons from K-12 CS education efforts

The mantra of "do not reinvent the wheel" is particularly pertinent to the K-12 AI education movement. Despite differences in the foci of topics and content taught, AI is essentially a sub-discipline of CS, in that there is no AI without computers. As such, even though there is an urgency to treat AI education and literacy as a special case, there is a lot of learning about how to address CS teaching and learning at the school level– an effort that is still ongoing and very pertinent to AI education [24]. These learnings include lessons on how to–**(1) center the learners**, their backgrounds, interests, and social eco-systems to ensure identity development and empowerment as a key outcome, **(2) create inclusive learning environments** that value all learners and motivate them to engage in AI as a subject/career **(3) incorporate important equity-oriented, inclusive teaching strategies** to reach learners from minoritized groups from the outset instead of adding them in as an afterthought, (This is especially relevant to AI and machine learning as it has been shown to disproportionately adversely impact underserved populations and people of color). **(4)** address the teaching of a technical discipline new to both teachers and students by leveraging **a plurality of pedagogies** such as project-, inquiry- and game-based learning, hands-on activities and explorations, games, unplugged activities, hands-on coding activities, **(5) address misperceptions** and inaccurate stereotypes of the discipline in order to promote interest and better learning among ALL students, **(6) attend to aspects of CT that are relevant to AI** to a larger (such as understanding data and its features and pattern recognition) or lesser (such as algorithmic thinking) degree and developing robust mental models (or notional machines) of AI, **(7)** focus not only to pedagogy and curriculum design, but also the means to **measure and assess student learning**, both formatively and summatively, **(8) build capacity among teachers and schools** to teach a new subject, **(9)** make room for, and reinforce the learning of, a cross-cutting topic through **integration into other subjects**, and **(10) educate stakeholders besides classroom teachers,** such as school and district administrators, on AI literacy so that they can help build supportive ecosystems in schools for AI education. Two of these are discussed in greater detail below.

Baking inclusion into AI teaching & learning, content, curriculum, pedagogy, and assessment. Although addressing the 'all' in 'CS for All' through targeted broadening participation efforts has been a major goal of K-12 CS, and there have been several champions for equity and inclusion in this movement, the needle has not moved as much as it needs to on equitable participation for minoritized populations and on attending to the needs of neurodiverse learners and learners with disabilities. As the movement (somewhat belatedly) redoubles efforts toward increasingly culturally relevant approaches to CS education to effect much-needed improvement in equity (e.g., [13, 51]) and gives more serious attention to developing inclusive technologies and pedagogies with high leverage practices, universal design for learning, and multiple entry points for learners [28], it should serve as a lesson for K-12 AI education. There is a need to go beyond the discussion of ethics and bias in AI to ensure that strategies for inclusive teaching & learning in content, pedagogy, and assessment are baked into AI curricula and tools from the outset.

Teacher preparation and integration into/ with other subjects. K-12 CS education has come to appreciate the crucial role that teachers play in the success of CSForAll efforts. As Strickland argues in [24], teachers' "pre-existing pedagogical and content expertise must be prioritized in the design of curriculum and PD experiences to prepare teachers to teach CS". Also, integration with other subjects using established frameworks (e.g. [21]) tackles the crowded curriculum problem and the goal to prepare all teachers regardless of the subject they teach. It also allows K-12 teachers, without specialized content knowledge, to leverage and use impactful pedagogies for ALL their students. There is a need to integrate AI into non-STEM core subjects as well. Teacher-led, exemplary resources for AI integration into subjects at various grade levels (such as [40]) are a valuable contribution to the field.

4.2 Closing Thoughts & Recommendations

In addition to the many lessons from ongoing AI education design and CS education research described in the preceding sections, here are closing thoughts and recommendations on how to tackle the seemingly challenging and monumental task of teaching AI as a subject to primary and secondary students–

Dovetail AIEd and CSEd efforts. One efficient and effective solution to address the paramount concerns of effective teacher preparation and making room in a crowded curriculum would be for the AI education efforts to work in cooperation (rather than opposition) with the existing CS education ecosystem, especially teacher PD providers, to prepare teachers on AI concepts and curricula and how they can be ***flexibly*** incorporated into existing CS curricula. There are examples of efforts that teach the basics of AI in high schools through a CS topics lens (e.g., [10]). Given the complexity of AI concepts, there is also a case for adjusting K-12 AI education goals to more directly provide foundational knowledge that will ***enable future*** AI learning [36]. This includes (among other competencies) data literacy and agency, critical thinking skills to evaluate thorny ethical dilemmas, and 'CT for AI' skills–all of which can be tackled in CS courses. This will require **revisiting and updating the K-12 CS standards** or a merging of sorts between the K-12 CS standards and the Five Big Ideas (and associated progressions). This effort appears to be underway [63].

Build an empirical base for age-appropriate progressions and inclusive pedagogies. In the short span of the last 5 years, an astonishingly large number of resources and detailed curricular materials have been developed. With this treasure trove of freely available AI resources and tools, develop new materials *only if you must*! The focus of K-12 research efforts would be better devoted to building scholarship focusing on inclusion and AI (1) learning & teaching in conjunction with current CS curricula, (2) integration into STEM, language arts, and social science education, (3) teacher PD, and (4) assessment. Additionally, the focus should be on examining which tools and activities can be used or adapted productively for various age groups, how sophisticated students' understandings are about the impacts of AI at various ages, and how/what can be taught (especially about the technical complexities of ML) with flexibility and multiple entry points at various grade levels to accommodate varied interest and ability.

It appears that we are at the dawn of a new discipline that combines computing, AI, data science, ethics, and the humanities. Until we figure it all out, educating students about AI will be the best strategy to ensure that they thrive in this brave new world and also the best inoculation against the misuse of AI. It is more important than ever, however, to do it in ways that ensure that ***it is humanity and the humans in the equation that matter above all else***.

5 ACKNOWLEDGEMENTS

This work is partly supported by NSF Grants 2113803 & 1949488.

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