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A framework for inclusive AI learning design for diverse learners

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ABSTRACT

As artificial intelligence (AI) becomes more prominent in children's lives, an increasing number of researchers and practitioners have underscored the importance of integrating AI as learning content in K-12. Despite the recent efforts in developing AI curricula and guiding frameworks in AI education, the educational opportunities often do not provide equally engaging and inclusive learning experiences for all learners. To promote equality and equity in society and increase competitiveness in the AI workforce, it is essential to broaden participation in AI education. However, a framework that guides teachers and learning designers in designing inclusive learning opportunities tailored for AI education is lacking. Universal Design for Learning (UDL) provides guidelines for making learning more inclusive across disciplines. Based on the principles of UDL, this paper proposes a framework to guide the design of inclusive AI learning. We conducted a systematic literature review to identify AI learning design-related frameworks and synthesized them into our proposed framework, which includes the core component of AI learning content (i.e., five big ideas), anchored by the three UDL principles (the "why," "what," and "how" of learning), and six praxes with pedagogical examples of AI instruction. Alongside this, we present an illustrative example of the application of our proposed framework in the context of a middle school AI summer camp. We hope this paper will guide researchers and practitioners in designing more inclusive AI learning experiences.

1. Introduction

Artificial intelligence (AI) was first defined in 1956 as "the science and engineering of making intelligent machines" (McCarthy, 2007). Ever since, many other definitions have arisen, such as the "science and technology of research and development of theories, methods, techniques, and application systems for simulating and extending human intelligence" (Wang, 2019) or "a branch of Computer Science combining Machine Learning, Algorithm development, Natural Language Processing" (Akgun & Greenhow, 2022). Recently, AI has progressively advanced and permeated all parts of our society, such as business, art, education, and medical fields, beyond the computing industry (Ng et al., 2021a), such as the ubiquity of AI in society has created a pervasive and profound impact on children's daily lives. According to the Childwise Monitor report, one in four children ages 5 to 16 live in households with a virtual assistant (Childwise, 2019). Children begin to engage with AI at a young age for many reasons, such as education, entertainment, and socialization. Children's perceptions of AI have evolved towards perceiving robots as sentient beings whom they can interact with, and are smarter than humans (Williams et al., 2019). For instance, one study found that children perceive a strong sense of social connection with a chatbot, viewing AI not only as a tool but also as a learning companion (Liu et al., 2022).

Despite their daily exposure to AI applications, young children are rarely aware of the concepts and mechanisms behind AI technology and potential ethical issues related to AI (Ghallab, 2019, Burgsteiner et al., 2016). Studies suggest that early exposure to AI learning enhances self-efficacy and the willingness to persist in AI learning (Song et al., 2023) and prepares them for future AI-related careers (Kim et al., 2023). On the other hand, a lack of AI literacy may prevent children from developing as creators, designers, and producers of future AI technologies (Ghallab, 2019, Burgsteiner et al., 2016), and may result in misconceptions or naive conceptions about AI, such as perceiving AI as a cure-all solution (Kim et al., 2023) or being overly fearful of AI (Cave et al.,

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2019). The latter misconception may prevent young people from considering AI-related careers (Bewersdorff et al., 2023).

Acknowledging the importance of AI literacy, governmental and non-governmental educational initiatives and research centers around the world have begun developing curriculum guidelines for K-12 AI education (i.e., teaching AI as a subject matter)[1] (Su et al., 2022, UNESCO, 2022). As an early effort, the AI4K12 initiative has organized its framework for K-12 AI learning based on the "Five AI Big Ideas" (Touretzky et al., 2019). While the Five Big Ideas framework outlines the foundational knowledge of K-12 AI education, more guidance is needed regarding how to effectively design and implement AI learning experiences that are both meaningful and inclusive (Yang, 2022, Gibellini et al., 2023).

The rapid and substantial transformation of the workforce driven by AI innovation (Ng et al., 2021a) underscores the importance of AI literacy as an essential competency for future citizens (Long & Magerko, 2020). Taking into account that today's learners are the future workforce (Vought, 2018), making AI learning more inclusive and accessible at the K-12 level is an essential step for broadening participation in AI careers, promoting diversity (Gibellini et al., 2023), and supporting economic advancement in related sectors of the workforce (Vought, 2018). This objective is supported by a growing body of research suggesting that diverse groups, encompassing various genders, races, and cultural backgrounds (among other variables), excel in conflict management within organizations (Lee et al., 2018) and are more likely to consider a multitude of perspectives in their decision-making processes, thus avoiding the pitfalls of group thinking (Gaither et al., 2018). In light of such research, there is a pressing societal call for more attention to equity and inclusion in K-12 AI education (Vought, 2018).

Despite the call for increasing diversity in AI-related disciplines (Vought, 2018), a lack of guidance exists at the K-12 level for designing inclusive AI learning experiences (Gibellini et al., 2023). Relevant to this gap in the literature, the aim of this paper is to propose a framework to guide the design and implementation of inclusive AI learning grounded in the principles of Universal Design for Learning (UDL). UDL is an interdisciplinary educational framework that centers on the creation of flexible and inclusive learning environments (CAST, 2018). It prioritizes catering to the diverse needs and abilities of all learners, regardless of their individual differences, thereby promoting equitable learning. In the context of K-12 education, UDL emphasizes the development of curricular materials, teaching methods, and assessment strategies that are accessible to all students, including those with disabilities and various learning preferences. While research on UDL in STEM contexts (e.g., computing education) has shown promise for reducing barriers to participation for diverse learners (Strickland et al., 2023, Israel, Ray, et al., 2017), scholars have yet to leverage UDL in support of inclusive AI learning design. Given that the application of the UDL principles should be carefully contextualized in specific domain areas (Almeqdad et al., 2023), there is a pressing need for a UDL-based framework specifically tailored for AI learning. To fill this gap, we propose a novel framework by synthesizing existing AI learning design frameworks and integrating them with UDL to make AI learning design more inclusive. To maximize our framework's practicality, we provide an example illustrating its application in the design of learning experiences within a conversational AI summer camp for middle school students.

2. Background

2.1. Universal Design for Learning (UDL)

UDL is a pedagogical framework that aims to make learning more inclusive for all students by proactively planning for the diversity in today's classrooms, including the range of backgrounds, abilities, and learning preferences (CAST, 2018). At its core, UDL recognizes that a one-size-fits-all approach to education is inherently limiting, and alternatively promotes the proactive design of tailored educational experiences (CAST, 2018). Specifically, UDL places a premium on honoring flexibility with the goal of dismantling barriers to learning and attending to the distinct learning needs of students with disabilities (Israel et al., 2020, Israel, Ray, et al., 2017). UDL also focuses on accessibility and leverages the use of assistive technologies to support these individuals' learning needs (Basham et al., 2010). As a framework for designing instruction, UDL promotes adaptable activities and assessments that empower learners to assume control over their learning. UDL-IRN (2011) underscores the importance of four critical elements in a UDL-based instructional environment: *clear goals, flexible methods and materials, intentional planning for learner variability*, and *timely progress monitoring*.

UDL draws its roots from architectural and product design fields. Alongside the passage of the Americans with Disabilities Act of 1990 (Public Law 101-336, 1990), the "universal design" movement captured the attention of architects and designers aspiring to create environments and products that were accessible to individuals with disabilities. This wave of inclusivity extended its reach into the education realm, aligning with the evolution of inclusive policies intended to enhance instructional accessibility (Israel et al., 2023). As such, this juncture marked the emergence of UDL as a pivotal force in fostering equitable learning and addressing the diverse learning needs of all students (Burgstahler, 2020). UDL's evolution is also linked with research in the field of cognitive neuroscience (CAST, 2018), which has made substantial advancements in unraveling the intricacies of how our brains process information. These strides include the identification of key neural networks responsible for various aspects of learning, such as attention, memory, and executive functioning. Notably, cognitive neuroscientists have elucidated the variability in individual learning profiles, shedding light on the diverse ways that learners absorb, process, and retain information (Yuan et al., 2017).

Informed by these insights, the Center for Applied Special Technology (CAST) developed a framework for UDL that has become prominently used in educational research and practices (CAST, 2023). The UDL framework is rooted in the following three guiding principles, which align with the key brain networks responsible for learning: Multiple means of representation (recognition networks; the "what" of learning), engagement (affective networks; the "why" of learning), and action and expression (strategic networks; the "how" of learning). Each principle plays a crucial role in fostering learning, prompting educators to provide multiple pathways for students to access information, engage with content, and express their knowledge and understanding. For instance, "multiple means of engagement" underscores the importance of providing diverse and motivating avenues for learning, focusing on students' varied interests, preferences, and backgrounds to help them sustain effort and persistence through self-regulation when learning becomes difficult. "Multiple means of representation" emphasizes the significance of providing content in a variety of formats and media, making the content accessible and comprehensible for all students. "Multiple means of action/expression" highlights the need to offer diverse options for students to express their knowledge, understanding, and skills, recognizing that learners differ in their abilities, preferences, and limitations when it comes to demonstrating what they have learned. Fig. 1 shows the CAST (2018) framework in its entirety.

These three interconnected principles collectively help educators create a dynamic and inclusive learning environment where learners are empowered to engage with, comprehend, and express their knowledge in ways that suit their individual needs and strengths. In honoring the inherent variability of learners by promoting flexibility, the UDL framework has established a common terminology and shared understanding regarding the design of inclusive instruction (McMahon & Walker, 2019). Numerous K-12 education policy initiatives in the United States have endorsed UDL, including the Every Student Succeeds Act (U.S. De-

[1] AI education is often compared with the concept of "AI in Education," which is often used to refer to utilizing AI as a learning tool (e.g., recommendation system). This paper focuses on teaching AI as a subject matter.

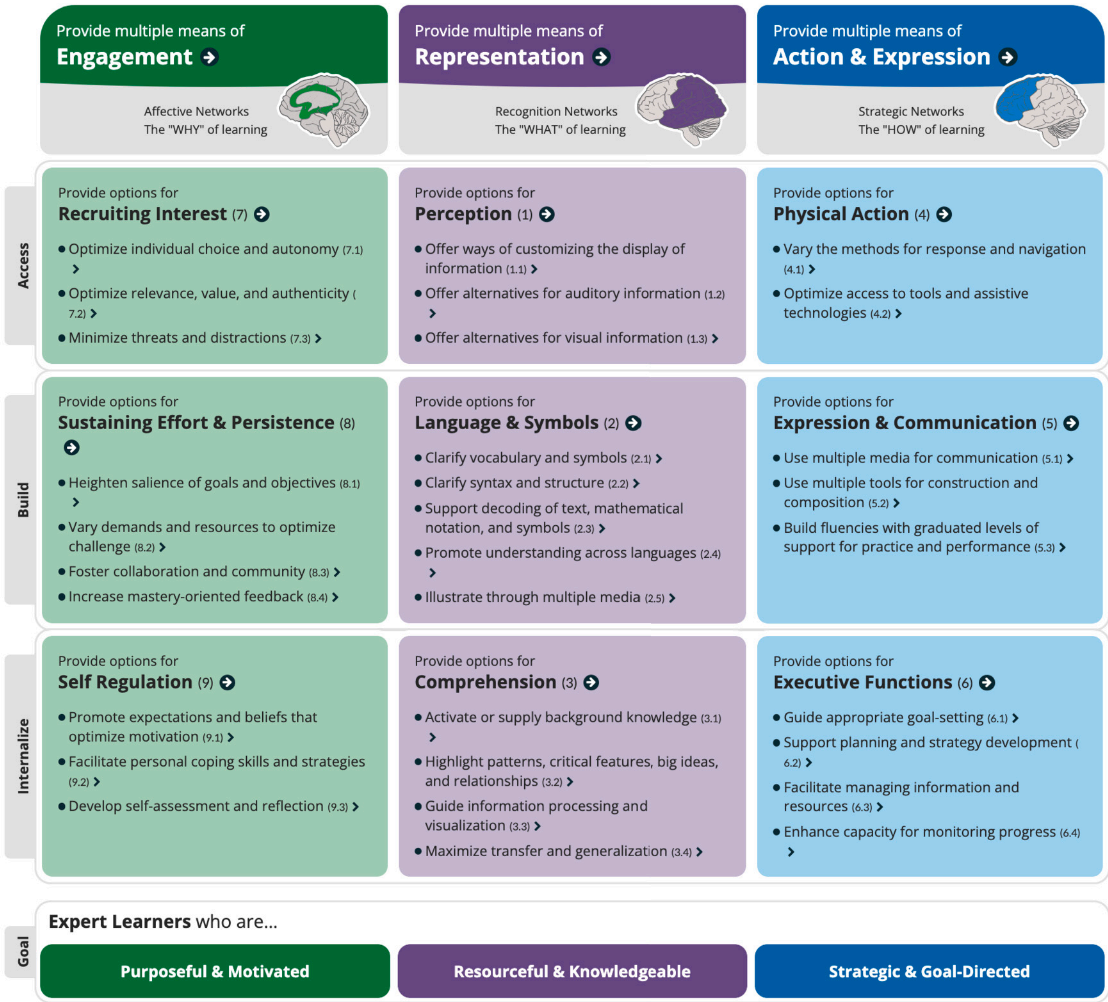

Fig. 1. Universal Design for Learning guidelines (CAST, 2018).

partment of Education, 2015), which requires that assessments align with UDL principles, the United States Higher Education Opportunity Act (U.S. Department of Education, 2008), which describes UDL as a "scientifically valid framework for guiding educational practices" (p. 110), and the National Education Technology Plan (U.S. Department of Education, 2017), which recommends applying UDL to promote accessible learning with technology. UDL has also gained international support for research and implementation, with European countries such as Belgium, Norway, and Spain engaging in UDL implementation efforts beginning in 2015, and New Zealand's Ministry of Education following suit in 2018 (McMahon & Walker, 2019).

2.2. UDL for inclusive AI learning design

UDL and technology have a symbiotic relationship in the literature. Technology has become a formidable ally in implementing UDL principles by enabling the creation of customizable and inclusive learning experiences (Israel et al., 2014, Rose et al., 2010). From adaptive software and online resources to interactive multimedia content, technology can serve as a facilitator of personalized learning, a cornerstone of UDL. Furthermore, the ubiquity of digital devices has expanded access to educational opportunities and materials, helping individuals with disabilities transcend physical barriers to learning. Although technology has been consistently harnessed to deliver UDL-enhanced instruction, the implementation of UDL in Science, Technology, Engineering, and Mathematics (STEM) education contexts has been limited. Furthermore, although scholars have advocated for adopting AI tools to support UDL implementation in the curriculum (Banes & Behnke, 2019, Bray et al., 2023, McMahon & Walker, 2019), limited attention has been paid to leveraging UDL to reduce barriers to participation and expand interest in AI-related subjects.

Our efforts to design inclusive AI instruction were largely influenced by the literature on UDL integration in computer science (CS) education. UDL's potential for increasing access and representation in CS at the K-12 and post-secondary levels is strongly supported by an emerging body of research (Hutchison & Evmenova, 2022, Lechelt et al., 2018, Marino et al., 2014, Wille et al., 2017). Central to these efforts, Israel, Lash, et al. (2017) developed a curricular crosswalk by adapting CAST (2011)'s framework to provide actionable guidance for addressing the "what," "why," and "how" of making CS education more inclusive. Their recommendations include representing information for learners using multiple modalities, symbols, and languages ("what"), recruiting learner interest by providing choices of projects or software ("why"), and facilitating learner action/expression using unplugged activities to physically represent abstract computing concepts ("how"). The disciplines of CS and AI education are intricately interwoven, as CS provides foundational framing, tools, and competencies necessary for developing and advancing AI technologies. However, AI education involves distinct knowledge and competencies that differ from traditional CS education (Long & Magerko, 2020). Supporting scholars' assertions that the application of UDL should be carefully contextualized within a domain area (Almeqdad et al., 2023), we are proposing a UDL-based framework specifically tailored for designing inclusive AI learning experiences.

3. Methods

3.1. Systematic literature review for AI education frameworks

We chose to conduct a systematic literature review to find, analyze, and synthesize existing literature on AI education in order to develop our novel framework. This decision was driven by the notion that there is no single dominant framework for AI learning design, whereas UDL's CAST framework has become widely applied across disciplines to guide inclusive learning (CAST, 2018). Our review was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework (Liberati et al., 2009). We conducted an initial search of research papers from the following relevant academic databases: ProQuest (encompassing ERIC, Education Database), EBSCO (encompassing Education Source, Academic Search Premier, APA PsycINFO, Teacher Reference Center), ACM Digital Library, Web of Science, Scopus, and IEEE Xplore. In addition, we hand-searched the following three journals that were recommended by two AI education experts serving as faculty at a Research 1 institution in the United States: Computers and Education, Computers and Education: Artificial Intelligence, and TechTrends.

We limited the time period of publications to the past 10 years (from 2014 to September 21, 2023) to broadly include recent educational research in the field of AI education, which began gaining researchers' interest after the emergence of Google's Alpha Go (Silver et al., 2016). We sought to identify peer-reviewed articles and conference proceedings broadly related to AI learning frameworks in the context of K-12 or general AI literacy for the public. Our search strategy consisted of the following keyword combinations: (AI OR "Artificial Intelligence") AND (education OR learning OR curriculum OR teaching) AND (K-12 OR K12 OR "AI literacy" OR "high school" OR "elementary school" OR child*) AND (framework OR "conceptual model"). The search string was reviewed and approved by the two aforementioned AI education experts.

We identified 521 potential articles for inclusion, which we downloaded and imported into the web-based software platform Covidence to manage the literature review process. After 157 duplicates were removed, 364 abstracts were screened for relevance using the following inclusion criteria.

1. Articles should present frameworks for AI learning design or approaches to AI education or AI literacy.
2. Studies should focus on AI learning in K-12 contexts or general AI literacy education for the public.
3. AI should be seen as the learning content (i.e., teaching AI).

Records were excluded based on the following criteria.

1. Papers included neither frameworks for AI learning design nor approaches to AI education or AI literacy.
2. Studies focused on higher education contexts or specialized AI education for experts.
3. AI was applied as a methodology (e.g., learning analytics) or used as a learning tool (e.g., recommendation system) in educational settings, rather than being the focus of the instruction.
4. Articles were not related to education (e.g., deep learning).
5. The presented frameworks are not novel (i.e., they are borrowed from previous literature).[2]
6. Papers were written in languages other than English, with no translation provided.
7. Conference posters or keynotes.

[2] In this case, we searched the original article and included that.

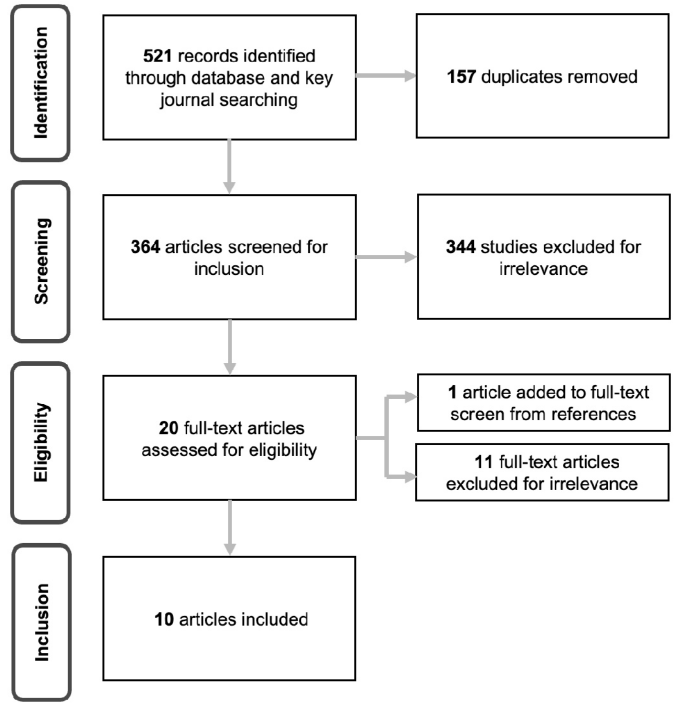

Fig. 2. PRISMA flowchart of the search and screening process.

Through the screening process, we specifically aimed to identify novel frameworks for AI learning design or approaches related to AI education. By "frameworks," we mean a visual representation (i.e., figure) that identifies key components (i.e., competencies, skills, beliefs) related to AI literacy or AI learning. By "approaches," we mean preliminary ideas to guide AI learning that may be valuable to include in our proposed framework (typically represented in the form of a table). The initial screening process involved a full-text scan to identify whether the articles included related figures or tables. To establish inter-rater reliability, two researchers independently engaged in full-text scans of 20% of papers. Inter-rater reliability was calculated using Cohen's Kappa, resulting in a coefficient of 0.90, indicating almost perfect agreement (Sim & Wright, 2005). The remaining conflicts were resolved through discussion. One of the researchers then proceeded to screen the remaining articles. Twenty records met all inclusion criteria and were assessed for eligibility with a full-text review conducted by both researchers. A snowball technique was used to include relevant articles that recurrently appeared in references within the relevant articles (Jalali & Wohlin, 2012). At the conclusion of this process, ten articles were identified as relevant and were thus included in our review. Fig. 2 visualizes the search and screening process.

3.2. Synthesizing multiple frameworks into a new framework

To develop our framework for inclusive AI learning design, we engaged in a synthesis of key components within the AI learning design frameworks and approaches drawn from the 10 relevant articles. Then, we organized these components into the "why," "what," and "how" of AI learning, in alignment with CAST (2018)'s UDL framework. The "why" of AI learning involves eliciting learner interest in AI, the "what" of AI learning encompasses the content related to building knowledge of AI, and the "how" of AI learning involves pedagogical strategies related to teaching AI.

4. Synthesis of literature

We identified ten articles related to AI learning through the systematic literature review. Below, we summarize each framework and approach from our review and describe how the components informed our novel framework by identifying the "why," "what," and "how" of learning from each framework and approach.

The "Five Big Ideas" framework is amongst the most frequently cited frameworks designed to guide educators in choosing "what" AI content to teach (Touretzky et al., 2019). The Five Big Ideas of AI are #1. computers perceive the world using sensors, #2. agents maintain models/representations of the world and use them for reasoning, #3. computers can learn from data, #4. making agents interact comfortably with humans is a substantial challenge for AI developers, and #5. AI applications can impact society in both positive and negative ways. These five ideas serve as a core content knowledge of K-12 AI education, driving AI learning across other frameworks, such as Ng et al. (2021b), Sun et al. (2023) and Su et al. (2022).

Chiu (2021) proposes a holistic model for AI curriculum design for K-12 schools based on interviews with 24 K-12 teachers. The model consists of the three main "content components" of AI education (i.e., *knowledge in AI, process in AI*, and *impact of AI*) and "praxes" (i.e., *student relevance, teacher-student communication*, and *flexibility*), with some example ideas (e.g., *authenticity* and *local understanding with a global perspective* under the praxis of *student relevance*). In addition to the "what" of AI learning (e.g., knowledge, process, and impact of AI), this framework attempts to provide a holistic view of the "why" of AI learning (e.g., relevance, authenticity) and the "how" of AI learning (e.g., teacher-student communication, flexibility).

Sanusi et al. (2022) proposes a conceptual framework of the following key components of AI learning: *knowledge* (i.e., skill, cultural), *learning* (i.e., cognitive, self-learning), and *team competency* (i.e., teamwork, human-tool collaboration). They also emphasize the importance of *ethics of AI* by situating it in the center of the framework. The components of this framework can be categorized into the "why" of AI learning (i.e., *teamwork, self-learning*), the "what" of AI learning (i.e., *skill, cultural knowledge, ethics of AI*), and the "how" of AI learning (i.e., *human-tool collaboration*).

Two frameworks (Ng et al., 2021b, Sun et al., 2023) in our review are rooted in the Technological Pedagogical Content Knowledge (TPACK) model, which highlights key competencies involved in effective teaching with technology (Mishra & Koehler, 2006). In the context of AI learning, "Technological Knowledge" involves understanding of learning artifacts, such as *hardware and software, AI-related agents, unplugged artifacts,* and *gamified* elements. "Pedagogical Knowledge" involves understanding of approaches like *discovery, inquiry-based learning, collaborative learning, constructionism, project/problem-based learning, unplugged activities,* and *hands-on/playful learning*. "Content Knowledge" involves an understanding of AI-related concepts such as *AI awareness, use of AI ethics, AI syllabus* (Russell & Norvig, 2010), and *Five Big Ideas about AI* (Touretzky et al., 2019).

Yang (2022)'s framework is potentially the most relevant to the notion of inclusive AI learning. Influenced by culturally responsive teaching, their framework emphasizes the "why" of AI learning by *establishing inclusion* (i.e., promoting collaborative and welcoming learning environments), *developing a positive attitude* (i.e., connecting AI activities with students' prior knowledge and familiar culture), and *enhancing meaning* (i.e. solving real-world problems using AI). It also addresses the "how" of AI learning by proposing *engendering competence* (i.e., providing various authentic assessments, such as artifacts, portfolios, and self-assessments). Built upon this work, our framework intends to provide a more holistic understanding of AI learning design encompassing the UDL principles and examples of AI pedagogy.

The following three articles include "approaches" to AI literacy and AI education with key components that are worth referring to when developing our framework. Yi (2021) conceptualizes AI literacy by suggesting three components: functional literacy, including *3Rs (Reading, wRiting, and aRithmetic)*; social literacy, including *social practice* and *critical thinking*; and technological literacy, including *technological intimacy* and *designing social future*. Next, Su and Zhong (2022) proposed an outline of AI curriculum design in the early childhood education context, with components like *AI knowledge, AI skills,* and *AI attitudes.* The components under each category are related to the "what," "how," and "why" of AI learning; *AI knowledge* addresses of "what" of learning, while *AI skills* is related to "how" and *AI attitudes* is connected to "why" of learning. Last, Casal-Otero et al. (2023) conducted a systematic literature review of AI literacy in K-12 education and generated a taxonomy of approaches to K-12 AI education. Casal-Otero et al. (2023)'s taxonomy includes "why" (i.e., *learning for life with AI*), "what" (i.e., *learning about how AI works*), and "how" (i.e., *learning tools for AI*) of learning.

Lastly, Long and Magerko (2020) presented AI literacy competencies and design principles. The competencies include learners' capability to answer the following essential questions: *what is AI?, what can AI do?,* and *how does AI work?*. While the competencies address the "what" of AI learning, the design principles address the "why" and "how" of AI learning. For instance, a design principle like "embodied interactions," meaning allowing learners to put themselves "in the agent's shoes" and experience embodied simulations of algorithms and hands-on experiments with AI technology, is closely related to the "how" of AI learning. Another design principle of "promote transparency," meaning to eliminate black-boxed functionality and improve documentation, also guides how AI should be taught.

Table 1 illuminates the synthesis process of literature on the above-summarized AI learning-related frameworks and CAST (2018) framework. We categorized the components in the alignment of the "why," "what," and "how" of learning, and the "selected components for our framework" in the last row of this table show the common components that we chose to include in our novel framework.

5. A new framework for inclusive AI learning design

Figure 3 features our novel framework for inclusive AI learning design. At its core lies the "AI Five Big Ideas" (i.e., Perception, Representation & Reasoning, Learning, Natural Interaction, and Societal Impact) (Touretzky et al., 2019), signifying their prominence as the key tenets of teaching AI in K-12 education. To facilitate inclusive pedagogy, the framework is anchored by the three UDL principles: multiple means of engagement (the "why" of learning), representation (the "what" of learning), and action & expression (the "how" of learning). Each principle is complemented by three corresponding praxes that draw their inspiration from UDL's guidelines and are visually distinguished by the predominant colors in CAST's (2018) framework of green, blue, and purple.

The outermost layer, which features examples of each principle's praxes within K-12 AI education contexts, was informed by our synthesis of AI learning design frameworks (see Table 1). These examples may relate to multiple praxes aligned with the same UDL principle, acknowledging the nuanced, multifaceted nature of AI pedagogy. For instance, within the "engagement" category, project-based learning may be closely associated both with the "Authenticity & Relevance" and "Collaboration & Community" praxes, contingent upon the contextual approaches adopted. Notably, the dashed circle enclosing the entire framework represents our intention for these examples to serve as starting points for AI learning design rather than confinements, as the field of AI continues to rapidly evolve. Below, we describe the praxes in our framework that align with each UDL principle.

5.1. The "engagement" praxes

The following praxes align with multiple means of engagement (the "why" of AI learning): "Authenticity & Relevance," "Collaboration & Communication," and "Self-regulation & Autonomy." These praxes provide diverse motivating avenues for AI learning to leverage students' varied interests, preferences, and backgrounds in order to help them sustain effort and persistence when learning becomes difficult.

Table 1
Synthesis of the UDL framework and AI education frameworks.

	Framework & Approaches	Why	What	How
UDL	The UDL Guidelines (CAST, 2018)	Provide multiple means of “Engagement” - Recruiting interest - Sustaining effort & Persistence - Self-regulation	Provide multiple means of “Representation” - Perception - Language & Symbols - Comprehension	Provide multiple means of “Action & Expression” - Physical Action - Expression & Communication - Executive Functions
AI Education	the Five Big Ideas (AI4K12, 2020)	-	Five big ideas: perception, representation & reasoning, learning, natural interaction, societal impact	-
	Holistic model to design AI curriculum for K-12 schools (Chiu, 2021)	Relevance; Authenticity	Knowledge in AI; Process in AI; Impact of AI; Graphical representation	Teacher-student Communication; Flexibility
	Framework for competencies for AI education (Sanusi et al., 2022)	Teamwork, Self-learning	Skill, cultural knowledge; Ethics of AI	Human-tool collaboration
	AI literacy TPACK Framework (Ng et al., 2021b)	Pedagogical knowledge (e.g., inquiry-based learning, collaborative learning, project/ problem-based learning)	Content knowledge (e.g., AI awareness, Use AI ethics, Five big ideas about AI)	Technological knowledge (e.g., hardware-/ software -based artifacts, AI-related agents, unplugged artifact, gamified elements)
	TPACK-based PD Framework (Sun et al., 2023)	Pedagogical knowledge: (e.g., project/problem -based learning)	Content knowledge (e.g., Five Big Ideas, Application of AI, AI ethics)	Technical knowledge (e.g., digital software, physical hardware to learn AI); Pedagogical knowledge (e.g., game-based learning, unplugged activities); Technical pedagogical knowledge (e.g., tools for teaching AI)
	The culturally responsive approach to AI education (Yang, 2022)	Establish inclusion (e.g., collaborative learning); Develop positive attitude (e.g., using cultural events); Enhance meaning (e.g., real-world issues, design project)	-	Engender competence (e.g., authentic assessment, timely feedback)
	Foundation of AI literacy (Yi, 2021)	Social literacy (e.g., Social practice)	Functional literacy (e.g., reading, writing, arithmetic)	Technological literacy (e.g., technological intimacy)
	AI curriculum design in early childhood education (Su & Zhong, 2022)	AI attitude (e.g., Collaborate with AI)	AI knowledge (e.g., Definitions & examples of AI; The Five Big Ideas of AI)	AI skills (e.g., Using AI tools, problem solving)
	Taxonomy of approach to AI learning in K-12 (Casal-Otero et al., 2023)	Learning for life with AI	Learning about how AI works	Learning tools for AI
	AI literacy competencies and design considerations (Long & Magerko, 2020)	-	What is AI?; What can AI do?; How does AI work?; How should AI be used?	-
		Contextualizing data	Graphical visualizations, simulations, explanations, interactive demonstrations	Embodied interactions, Unveil gradually, Promote transparency
Selected components for our framework		- Project/ problem-based learning - Personally-relevant project design - Collaborative learning - Self- and peer-evaluation	- Graphical visualizations - Simulations - Interactive demonstrations - Explainability - AI five big ideas (learning content)	- AI unplugged activities - Developing artifacts using AI tools (digitally and physically) - Authentic assessment - Individualized facilitation - AI project documentation

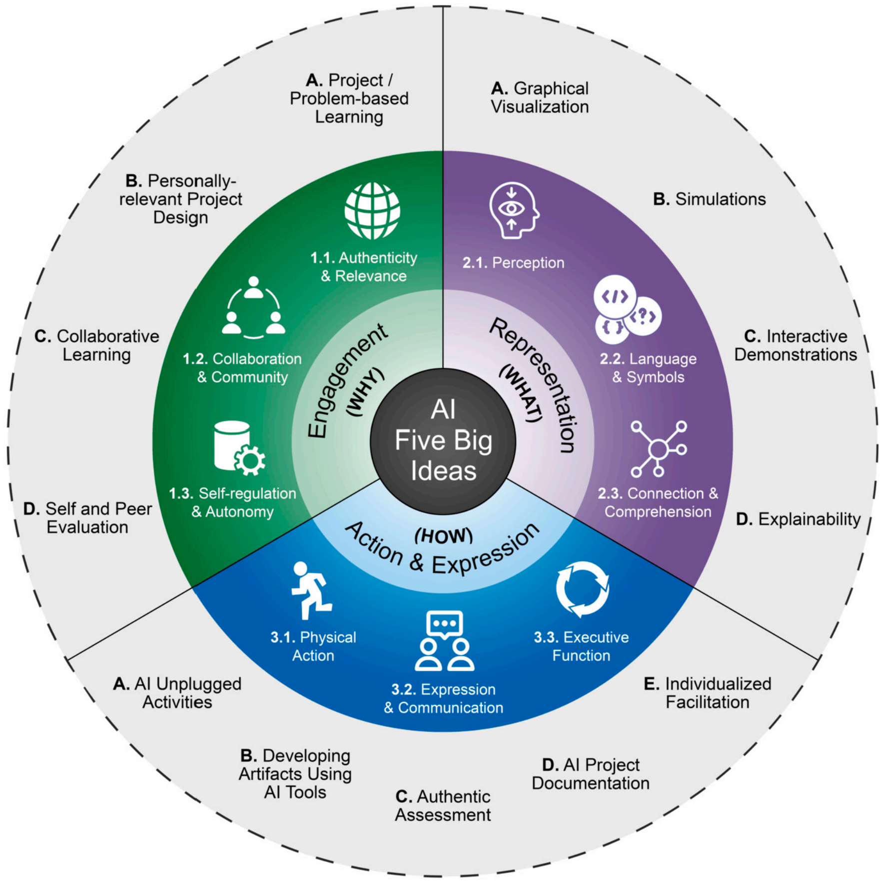

Fig. 3. New framework for inclusive AI learning design.

5.1.1. Authenticity & Relevance

Optimizing relevance and authenticity is an effective way to recruit learners' interest (CAST, 2018). To best engage learners, learning activities should be personalized and authentic to learners' lives. For example, they should be appropriate for learners' age, race, gender, ability, and cultural background. For instance, utilizing *A. project-based learning or problem-based learning (PBL)* can promote authentic AI learning, especially when learners devise ways to use AI technologies to solve a real-world problem (Ng et al., 2021b, Sun et al., 2023). While leveraging PBL, it is also important to support learners in *B. personally relevant project design* to maximize the relevance of instruction and allow learners to use their imagination to solve relevant problems in creative ways (CAST, 2018).

5.1.2. Collaboration & Community

Supporting collaboration and community is a recommended strategy to sustain learning efforts and persistence (CAST, 2018). Students can develop AI literacy by forming different types of relationships with their peers in the classroom. For instance, constructing AI-focused learning communities and providing *C. collaborative learning* opportunities geared towards AI literacy with peers who share common interests could be effective ways to foster engagement in AI learning.

5.1.3. Self-regulation & Autonomy

Self-regulation is one of the critical constructs to sustain learning and a deliberately designed level of autonomy is one of the important foundations for developing self-regulation. In AI education, students can have an opportunity to foster self-regulation and autonomy by conducting *D. self and peer evaluations* of their learning artifacts. After the evaluation, learners would have time to reflect on their learning and set the next goal or adjust their goals.

5.2. The "representation" praxes

The following praxes align with multiple means of representation (the "what" of AI learning): "Perception," "Language & Symbols," and "Connections & Comprehension." These praxes emphasize providing content related to AI literacy in a variety of formats and media, making it accessible and comprehensible for all students.

5.2.1. Perception

Effective learning happens when the information is easily perceived. Because AI is a new topic for most learners, it is important to present information in different modalities (e.g., text, sound, images) and flexible pathways (e.g., adjusting the text size). In AI education, it is often essential to present how technology works in effective and varied ways, such as *A. graphical visualization, B. simulations,* and *C. interactive demonstrations*. For example, learning technologies, such as Teachable Machine[3] can be useful in supporting learners' perceptions of how AI works.

5.2.2. Language & Symbols

For learning to be accessible and comprehensible for all learners, learners' language and cultural backgrounds must be considered. In AI learning contexts, there may be many essential terms or phrases that young learners are not familiar with in their daily lives, such as "machine learning," or "training data." Therefore, it is important to scaffold instruction by explaining these terms right away, before transitioning towards higher-level learning activities. In addition, using *A. graphical visualization, B. simulations,* and *C. interactive demonstrations* can also support learners' understanding of AI-relevant languages and symbols.

[3] https://teachablemachine.withgoogle.com/.

5.2.3. Connections & Comprehension

To support learners in constructing usable knowledge, it is important to provide ways for them to connect with prior knowledge and guide their information processing. One of the barriers to AI learning and comprehension derives from black-box models of AI (Khosravi et al., 2022), which prevents learners from fully understanding the underlying mechanism of an AI model's decision-making. Therefore, it is important to prioritize the *D. explainability* of AI, such as visualizing the decision-making processes of AI models within learning technologies.

5.3. The "action & expression" praxes

The following praxes align with multiple means of action and expression (the "how" of AI learning): "Physical Action," "Expression & Communication," and "Executive Function." These praxes offer diverse options for students to express their knowledge, understanding, and skills related to AI literacy.

5.3.1. Physical Action

Interactive learning activities involving dynamic physical actions provide more joyful learning experiences (CAST, 2018). For instance, in CS education, "unplugged" activities have been used to introduce CS concepts to novice learners using various physical actions without using computers (Bell et al., 2005). The AI education community is also taking advantage of this strategy by developing AI-unplugged activities (Ma et al., 2023, Long et al., 2021). *A. AI unplugged activities* help learners who do not feel comfortable with computers have easy and formidable access to AI education. In addition, *B. developing artifacts using AI tools* is another way to engage learners in physical action. When designing these activities and tools, it is important to make sure they are accessible to learners with different physical abilities and preferences.

5.3.2. Expression & Communication

Individual learners hold strengths and weaknesses in different modalities to express their knowledge and communicate (CAST, 2018). Thus, learners should be provided with alternative modalities for expression, especially in the context of assessment, where in progressive *C. authentic assessment* is prioritized over traditional paper-and-pencil tests. In AI education, authentic assessment could include the summative evaluation of students' AI artifacts (e.g., chatbots), or formative approaches, such as cognitive interviews where students can express their knowledge and gamified assessments of AI knowledge using tools like Kahoot!.[4]

5.3.3. Executive Function

Executive function refers to the ability to set long-term goals, monitor one's own behaviors, and enact strategies to obtain goals (CAST, 2018). In contexts where students engage in long-term AI development projects, well-designed scaffolding, and individualized facilitation are necessary to support the successful planning, managing resources, and monitoring processes. Relevant to this notion, we suggest providing tools for *D. AI project documentation*, which helps learners document their long-term goals, step-by-step strategies, and reflections during the AI project activities. In addition, *E. individualized facilitation* is essential to provide learners with timely feedback and scaffolding.

6. Illustrative example: "Camp Dialogs" learning experiences

In this section, we provide an illustrative example of how our novel framework can support inclusive AI learning within the context of an AI summer camp for middle school students called Camp Dialogs. Camp Dialogs aims to engage rising 7th and 8th graders in AI learning by empowering them to create personally relevant AI artifacts (i.e., chatbots), which have become increasingly common in the lives of today's tech-savvy youth, using custom-designed development software called "AMBY (AI Made By You)" (Tian et al., 2023). The idea behind this instructional approach is to anchor AI learning within familiar experiences for students. It has become commonplace for children and teens to engage with AI chatbots in everyday tasks, such as seeking assistance from Alexa for their homework or requesting their favorite tunes (Garg & Sengupta, 2020). By learning how to design this form of conversational AI, learners are introduced to foundational AI concepts that underpin the Five Big Ideas (Touretzky et al., 2019), such as understanding computers' perception of natural language, the need for training data sets, and AI-human interaction design (Song et al., 2023). Through three years of iterative design and implementation process, the camp experience was universally designed to increase accessibility and relevance for learners from diverse backgrounds, irrespective of their prior knowledge, skills, interests, or experiences. The outcomes of the camp, involving 32 participants, demonstrate significant improvements in learners' ability, beliefs, willingness to share their knowledge, and persistence about AI learning from pre-to-post surveys (Song et al., 2023).[5] In the following sections, we describe how the camp's learning activities and the software interface design utilized in this camp align with aspects of our proposed framework.

Fig. 4 illustrates an exemplary application of the inclusive AI learning design framework in the context of the "Camp Dialogs" program learning design. While the camp lessons and activities are designed to cover several of the AI Five Big Ideas (e.g., # 2. representation & reasoning, #3 learning), the main learning activities around the conversational app development project focus on the big idea #4. natural interaction (placed at the core of Fig. 4). The newly added outer circle with light colors represents the learning activities in Camp Dialogs that align with our inclusive framework.

6.1. "Engagement" (WHY)

In the Camp Dialogs program, students engage in the conversational app development project. This project activity promotes authenticity and relevance to the students by leveraging project-based learning (1.1. *Authenticity & Relevance - A. Project-based Learning*). Prior to the project development, learners participate in a chatbot brainstorming session (Fig. 5.a), where they generate ideas based on their interests. During the project, students engage in pair programming where students and the work on the same computer and switch roles between the *driver* (who types) *navigator* (who observes and suggests) periodically during the task (Campe et al., 2020) (Fig. 5.b). Pair programming is a popular collaborative learning approach in CS education that has demonstrated mostly positive outcomes, such as increased project quality and engagement (Bowman et al., 2020). In the context of our framework, pair programming fosters collaborative learning (1.2. *Collaboration & Community - C. Collaborative Learning*), enriching communication and knowledge sharing. Learners collaborated with peers who shared similar interests to develop personally relevant and meaningful ideas for their chatbot (1.1. *Authenticity & Relevance - B. Personally-relevant Project Design*). For example, a pair of Black students developed a chatbot that teaches about Black history, while a pair of students who were twins collaborated to create a chatbot that provides facts about twins. At the culmination of the development process, learners engaged in self and peer evaluations (1.3. *Self-regulation & Autonomy - D. Self and Peer Evaluation*) of each other's projects in small groups based on a provided checklist (Fig. 5.c).

[4] https://kahoot.it/.

[5] For more information about the iterative design and evaluation of the outcome of the summer camp, please refer to Song et al. (2023), Katuka et al. (2023).

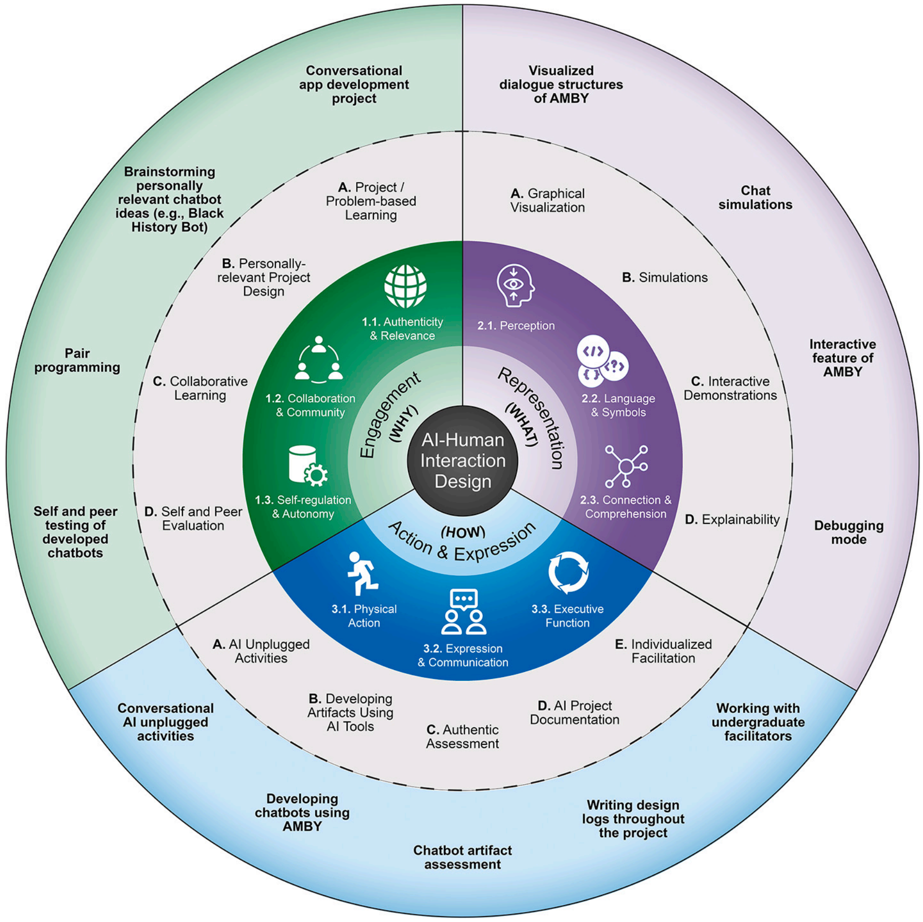

Fig. 4. Application of the framework to "Camp Dialogs" program.

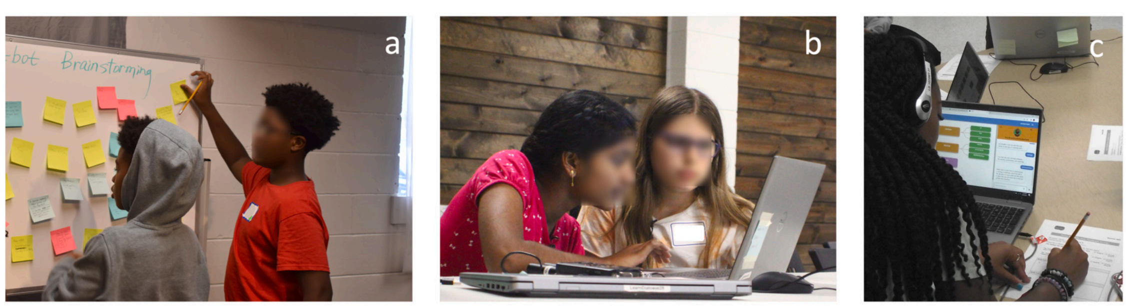

Fig. 5. Conversational app development activities during the summer camp (Photo release has been obtained from the participants.) a) Learners brainstorm about chatbot ideas using sticky notes; b) Learners work collaboratively on developing a chatbot; c) A learner engages in project testing and gives peers feedback.

6.2. "Representation" (WHAT)

To provide an engaging and accessible learning experience, a technology called AMBY that supports students' development of their chatbots was devised, aligns with our framework by providing a set of AMBY a set of sample projects that students can use as interactive demonstrations (2.1. *Perception* - *C. Interactive Demonstrations*) to test and tinker with before they start their own projects. When the students create their own chatbots, they can customize the name and avatar that represent their agent. The main development page utilizes graphic visualization to represent the dialogue structure of the conversational agent (2.1. - *Perception* - *A. Graphic Visualization*). For example, Fig. 6 shows the aforementioned project created by twins called "twinnem." In the conversation tree of the "development panel," the colored boxes represent user intents, which are created by the developer (i.e., learner) to capture the intention of various user expressions (e.g., "greeting," "asking for help," "learning about facts"). Intents are colored differently (in yellow, purple, and green) to represent their unique properties and to ensure optimal visibility through emphasized color contrast (2.1. - *Perception* - *A. Graphic Visualization*). This design consideration not only aids in distinguishing between different types of intents but also enhances the user experience, especially for those with visual impairments. The size of the conversation tree and text in the box is adjustable to support accessibility.

On the "chat simulations panel" (right), learners can test the agent instantly while editing the intents (2.2. *Language & Symbols- B. Simulations*). In the user text entry box, there is a microphone button that enables voice-based interaction. By turning on the speaker, the agent's utterances are presented with sounds, allowing learners to have a verbal interaction with the agent (2.2. *Language & Symbols*). AMBY also offers the AI model's explainability (2.3. - *Connection & Comprehension* - *C. Explainability*); By clicking the "debug" button, learners can enter

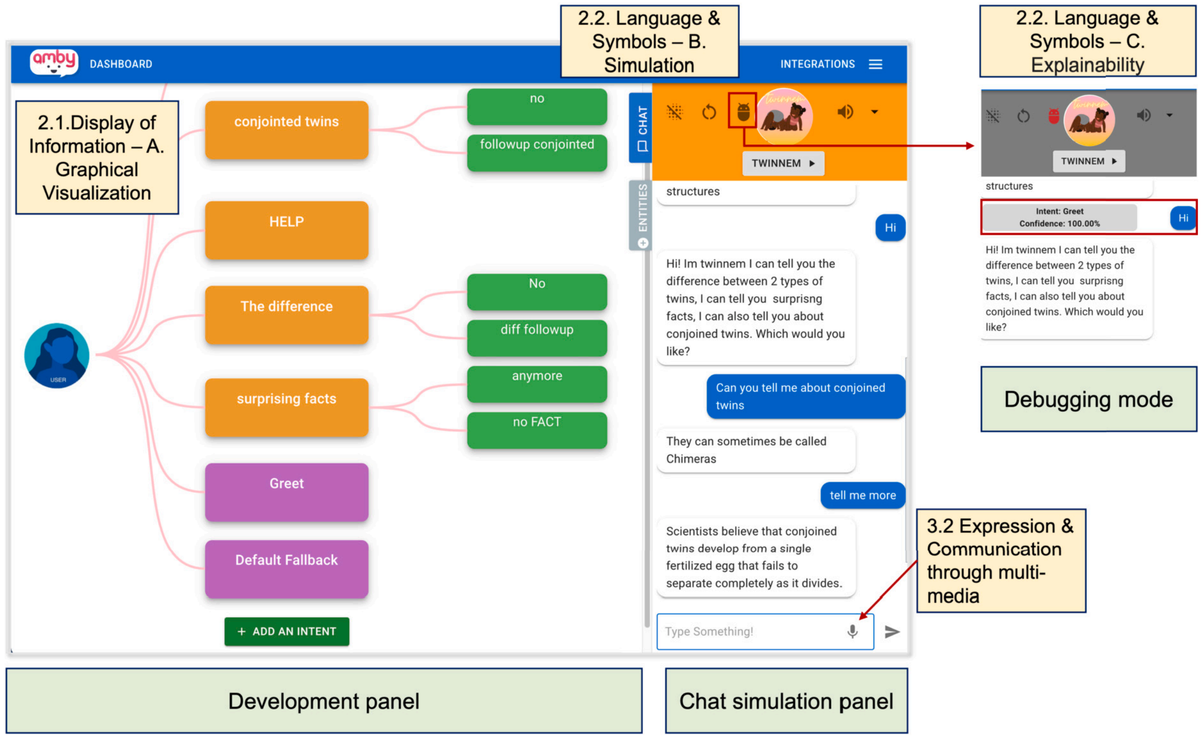

Fig. 6. AMBY's development page. Bordered boxes are annotations of the interface, light green boxes indicate the functionality of different panels, and yellow boxes indicate its direct connection with our proposed framework.

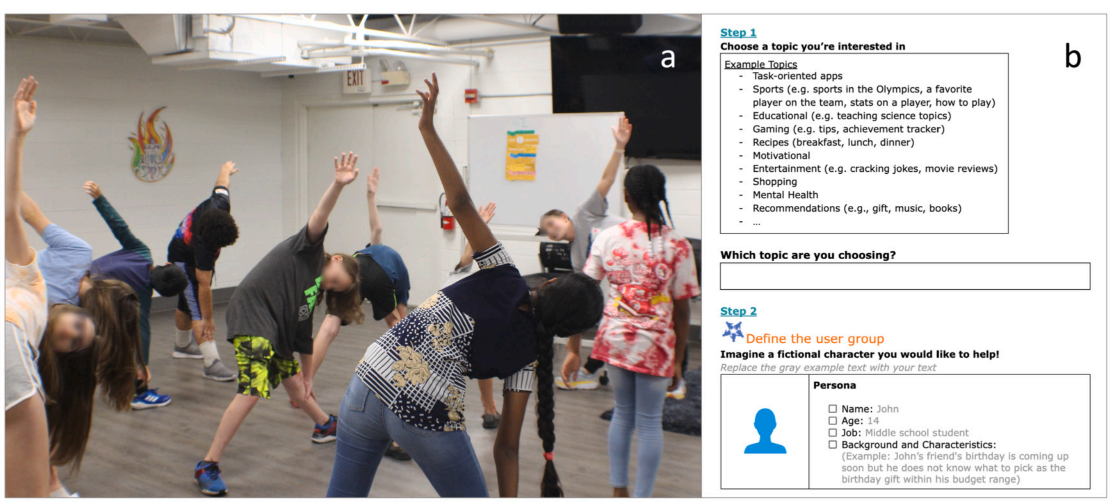

Fig. 7. a) Learners engage in an Unplugged activity; b) Conversational app design log.

a debugging mode (shown in the right figure). Within this mode, they can examine the intent classification results and the confidence levels associated with each user expression generated by the AI model. Fig. 6 presents AMBY's interface with an annotation of how each component is aligned with the proposed framework.

6.3. *"Action & Expression" (HOW)*

Camp Dialogs' program deploys a variety of activities that encourage learners to express their knowledge, understanding, and skills in AI. First, before delving into the AI lessons, students are introduced to basic AI and conversational AI concepts through unplugged activities. Stemming from CS education, unplugged activities are designed to teach CS concepts to novice learners without using computers (i.e., "unplugged.") (Bell et al., 2005). In the Camp Dialogs program, a series of AI-unplugged activities were devised to engage learners in different physical activities, such as playing with Lego, yoga, and acting (Fig. 7.a).[6] These unplugged activities were designed to reflect the principles of 3.1. *Physical Action - B. Developing Artifacts Using AI Tools*. In addition, as mentioned above, the main conversational app development project activity supports 3.1. *Physical Action - B. Developing Artifacts Using AI Tools*. In addition, to support the conversational app development activity, AMBY offers voice-to-text as an input modality to reduce the barrier of typing (3.1. *Physical actions*, 3.2. *Expression & Communication* through multi-media). During the project's development, a facilitator was assigned to each pair of students to provide individu-

[6] For more information and detailed instruction of AI-unplugged activities, please refer to Song et al. (2024).

alized feedback and optimized scaffolding (3.3. *Executive Function - E. Individualized facilitation*). To support their chatbot development processes, we provided a design log that guided learners through the stages of Design Thinking (i.e., Empathize, Define, Ideate, Prototype, Test) (Thoring et al., 2011, Arık & Topçu, 2020) (Fig. 7.a). This document was devised based on the UDL principle of 3.3. *Executive Function - D. AI Project Documentation*. The final learning artifact (e.g., the chatbots) was holistically evaluated based on a rubric (3.2. - *Expression & Communication - C. Authentic assessment*).

7. Conclusion

In a society where AI is becoming increasingly prevalent (Ng et al., 2021a), making AI learning more inclusive and accessible for all learners is an important step for the advancement of the AI field and promoting equity in society (Vought, 2018). Toward this goal, this paper proposes a novel framework for inclusive AI learning design grounded in recent literature on AI learning and the principles of UDL. The proposed framework has “AI Five Big Ideas” at its core and emphasizes inclusivity by grounding itself in the three UDL principles (i.e., engagement (“why”), representation (“what”), and action & expression (“how”). Under each of related AI pedagogy UDL principle are three praxes with multiple examples of AI pedagogy. In addition, this paper provides an illustrative example of the framework’s application in the context of K-12 AI education.

The proposed framework highlights the following three points of significance. First, the framework is created based on the systematic review of recent literature on AI education. As pressing as it is to design and implement AI learning experiences and curricula in K-12 education, there have not been many frameworks that guide learning designers and teachers in the design of inclusive AI instruction (Gibellini et al., 2023). Relevant to this gap, this paper synthesized the existing frameworks and approaches into one framework. Second, this framework showcases an example of an application of UDL in AI education. The CAST (2018) framework guides making learning more inclusive across disciplines. However, for practical usage, it is important to contextualize the UDL principles in specific domains (Almeqdad et al., 2023). This paper is an attempt to support the application of the UDL in K-12 AI education. Lastly, this paper intends to maximize the practicality of the proposed framework by providing example pedagogies (i.e., the outermost layer of the framework in Fig. 3) and an illustrative example of AI summer camp design. The Camp Dialogs example illustrates the real-world application of our framework in terms of the activity design and learning technology interface design.

Because AI is an emerging field and teaching AI has recently begun to be discussed in the education community, there was a relatively small number of articles included in our review. At this point, this framework serves as an entry into inclusive AI learning design that we expect will evolve alongside rapid changes within the field of AI. As we mentioned, the outermost circle of the framework (Fig. 3) has a dashed line with the intention to imply that these examples are not fixed and rather expected to be changing and evolving. Second, there could be some logistical hardships or burdens for the teachers to implement the suggested guidelines of the framework. The illustrative example in section 6 is situated in an informal learning setting, where learning designers could have more autonomy to control the learning environment. For instance, *individualized facilitation* could be less realistic for a formal classroom setting with limited resources where one teacher needs to lead the whole class. Third, while this framework targets K-12 learners broadly, teachers or learning designers would need to make adjustments to each component and its relative importance to best serve their learners. For example, for younger learners who have not developed abstract thinking skills (i.e., concrete operational stage; ages 7-11, according to Piaget (1955)’s theory), more emphasis should be placed on components such as *interactive demonstrations* and *unplugged activities*. Following the idea of UDL, this framework does not intend to provide a cure-all solution to inclusive AI learning and requires users to be flexible when applying this. Lastly, our illustrative example (section 6) provides only a use case with a certain situation (e.g., geographical location). More empirical studies are needed to utilize the proposed framework to design AI learning experiences (e.g., curriculum, learning technology interfaces) to evaluate its applicability and gain insights to improve it. We hope that this framework will be applicable to diverse learners in broad grade levels and geographical locations.

List of acronyms

AI	Artificial Intelligence
UDL	Universal Design for Learning
CAST	Center for Applied Special Technology
STEM	Science, Technology, Engineering, and Mathematics
CS	Computer Science
TPACK	Technological Pedagogical Content Knowledge
PBL	Project-Based Learning or Problem-Based Learning

Statements on open data and ethics

The data supporting the findings of this paper are available from the corresponding author upon reasonable request. Regarding the example case presented in the paper, the study was approved by the [Author’s institute’s] Institutional Review Board (IRB202100031, IRB202300786). No personal identifiers were reported in this paper.

CRediT authorship contribution statement

Yukyeong Song: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Data curation, Conceptualization. **Lauren R. Weisberg:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Conceptualization. **Shan Zhang:** Methodology, Data curation. **Xiaoyi Tian:** Writing – original draft. **Kristy Elizabeth Boyer:** Writing – review & editing, Supervision. **Maya Israel:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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