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Informal STEM Learning as a Pathway to Youth's AI Literacy: A Mixed Methods Study

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ABSTRACT

Informal STEM learning (ISL) is a blueprint for learner-centered experiences grounded in hands-on, real-world, and semistructured activities. ISL engages youth in complex disciplines (e.g., engineering and computer science) while building confidence, self-efficacy and persistence in STEM. As artificial intelligence (AI) becomes increasingly accessible, youth emerge as early adopters. Researchers and practitioners can utilize ISL to support youth AI literacy. This study implements Ng et al.*'s (2023) ABCE Framework and the AI Literacy Questionnaire to analyze baseline AI literacy among 104 youth aged 12–17 from three summer camps. An interpretive phenomenological analysis of youth's perception of AI systems was conducted through semistructured interviews. Drawing on findings and the literature, I argue that ISL is an effective approach to developing youth's AI literacy.*

Keywords: AI literacy, Camps, Informal STEM learning, Mixed methods

INTRODUCTION

STEM education is a proven interdisciplinary approach that has resulted in multiple benefits for youth. Decades of research have demonstrated that STEM education supports gains in youth's academic achievement and conceptual understanding across both STEM and non-STEM disciplines (Sungar et al., 2023). While also strengthening skills such as digital literacy, critical thinking, creativity, STEM competencies, and engineering design skills (Golegou et al., 2026; Sungar et al., 2023), STEM education increases youth's interest and motivation toward STEM careers; improves attitudes toward STEM; provides authentic, inquiry-based, and active learning experiences; raises awareness of equity and social justice; and reduces the likelihood of school dropout (Sungar et al., 2023).

Despite its documented benefits, traditional formal STEM education faces several persistent challenges. Alongside growing pressure to increase the number of STEM graduates to meet workforce demand, shortages of STEM-trained educators, limitations in assessment practices, and insufficient teacher support, ongoing pedagogical and curricular constraints become barriers to these benefits (Golegou et al., 2026; Sungar et al., 2023).

In response to these barriers, informal STEM learning (ISL) emerged as a complementary approach for expanding access, flexibility, and engagement in STEM education. ISL offers a multitude of opportunities "to participate in legitimate scientific and technological practices and ways of being beyond traditional curricular structures and constraints" (Greenberg et al., 2023, p.28). ISL environments are typically outside of school, ranging from "short-intervention experiences such as a half day hands-on workshop or day-long museum experiences to week-long day camps held at schools or universities" (Mohr-Schroeder et al., 2014, p.292). ISL does not face the challenges and limitations of traditional STEM education (Mohr-Schroeder et al., 2014). Through enhanced learning experiences filled with hands-on, real-world, semistructured activities, ISL offers youth opportunities to engage more deeply with complex disciplines such as engineering and computer science. It is a familiar approach that researchers and practitioners can use in developing youth AI literacy.

Because of its proven track record with complex disciplines in STEM and computer science education, ISL can provide researchers and educators with a blueprint for artificial intelligence education, which is both a complex and abstract concept. Currently, adoption of AI technology among youth has grown from 61% in 2024 to 84% in 2025 (Hanover Research Reports 2024 and 2025). In a recent study by the Pew Research Center, 54% (2025) of youth aged 13-17 use AI chatbots, such as ChatGPT, to help them with schoolwork, which has more than doubled since 2024 (McClain et al., 2026; Sidoti et al., 2025). In this same study, youth reported using AI chatbots to research a topic (47%), to solve math problems (43%), and to edit their writing (35%). An AI chatbot not only provides youth with academic help but also provides entertainment, which is supported by 47% of youth reporting using it for fun or entertainment (Maheux et al., 2026; McClain et al., 2026). With youth's increasing adoption of AI, their AI literacy and the conceptual knowledge needed to understand the technology and its societal implications are being indirectly shaped. There is an urgent need to support youth in navigating the entangled benefits (e.g., personalized learning) and harms (e.g., data privacy) associated with using this technology (Akgün et al., 2026; Basha, 2024; Bit et al., 2024; Long et al., 2021).

Researchers have approached these challenges by developing AI curriculum guidelines (Touretzky et al., 2019), AI literacy frameworks (Chiu et al., 2024; Long & Magerko, 2020; Ng et al., 2021), and tools used to enhance the learning environment, such as personalized learning, intelligent tutoring systems, and automated grading and feedback systems (Bit et al., 2014, Ng et al., 2022). However, support that only tells youth what to learn lacks structured guidance and concrete opportunities for youth to take informed action (Giansanti & Cosenza, 2026; Landesman et al., 2026). Currently, there is limited empirical research where these guidelines, frameworks, and tools are applied in practice and are not informed by youth perceptions of AI systems.

By applying an explanatory sequential mixed methods design (QUAN → qual), the research team, consisting of one researcher and two PhD students, explain why ISL is an effective approach to develop youth's AI literacy by applying research to practice. The following research questions guided our research design and analysis:

- What is youth's baseline AI literacy prior to starting camp?
- What is youth's perception of AI technology and systems after completing camp?
- How can youth's baseline AI literacy and perceptions of AI technology and systems inform what informal STEM learning practices support youth's AI literacy?

We implemented Ng et al.'s (2023) ABCE framework to analyze the results from the AI literacy questionnaire (AILQ) administered to 104 youth participants across three ISL-designed summer camps. Our survey findings established baseline data on youth AI literacy. We used an interpretive phenomenological analysis for eight semistructured interviews and one focus group interview to further explain the quantitative results and to provide context through centering youth's perceptions of AI and personal experiences. This work significantly contributes to the current AI literacy literature by demonstrating the application of research to practice, promoting ISL practices that inclusively engage youth's critical awareness of self and society in developing AI literacy, and advancing interdisciplinary collaboration with STEM educators and researchers whose subject matter expertise provides transferable attributes for youth's AI literacy development.

LITERATURE REVIEW

Informal STEM Learning

According to Coombs and Ahmed (1974), informal learning is the “lifelong process by which every person acquires and accumulates knowledge, skills, attitudes, and insights from daily experiences and exposure to the environment – at home, at work, at play” (p.262). Building on the foundational ideas of Combs and Ahmed, Morris et al. emphasize that ISL is not only rooted in everyday experiences but is also driven by learners’ curiosity, exploration, play, and collaboration, which serve as the primary drivers for acquiring knowledge, skills, attitudes, and developing STEM identities (Barker et al., 2014; Morris et al., 2021). They argue that when ISL experiences create space for curiosity, play, and collaboration with peers, mentors, or caregivers, learners are better able to coconstruct knowledge within social contexts (Morris et al., 2021).

Additionally, ISL produces “authentic activities” where productive failure, guided play, and social interaction coexist (Morris et al., 2021). An example is Digital Youth Divas, a 2-year after-school program for middle school-aged African American girls and Latinas, which offered a project-based curriculum that entwined computational and digital literacies through integrating circuitry, fabrication, programming, and design, where learners transformed everyday objects and practices into unique artifacts (Pinkard et al., 2014). This program intentionally centered girls as designers, programmers, electrical engineers, and computer scientists; dedicated time for collaboration and conversation; and provided mentorship to support learners' technological fluency, program and project completion skills and provide insight into future careers in STEM (Pinkard et al., 2014).

Building on this example, the current literature supports Pinkard et al.’s claim by suggesting that ISL experiences can increase interest in STEM, encourage students to pursue STEM-related coursework in high school, and positively impact their classroom learning and engagement (Anand and Dogan, 2022, Barker et al., 2014, Cian et al., 2022, Kramarczuk et al., 2023, Mohr-Schroeder et al., 2014). Through informal STEM learning experiences, learners are given stepping stones toward paths that lead to STEM and computing degrees and careers (Kramarczuk et al., 2023; Mohr-Schroeder et al., 2014). For example, Kramarczuk et al.’s (2023) longitudinal study of 9 alumni of a 3-year summer informal STEM learning experience called CompSciConnect revealed that near-peer mentorship, parental influence, and social interaction with other girls who shared similar interests contributed to their self-confidence and self-efficacy to persist in computing in high school and into college (Kramarczuk et al., 2023). In this example, ISL had a positive impact on learners, lasting well past the initial experience.

While these outcomes demonstrate the success of ISL, persistent barriers of oppression still exist for girls and youth from historically underrepresented groups in STEM. Morris et al. (2021) and Greenberg et al. (2025) highlight the need to reimagine ISL as a more culturally relevant and collaborative process. In this view, ISL is further enhanced through successful mentorship and caregiver relationships. Mentors who share identities with their learners and caregivers can influence learners' self-efficacy, areas of interest and facilitate mastery in a content area.

An example that illustrates this shift in ISL is COMPUGIRLS, a five-week summer program that met twice a week during the school year, where Black or African American girls and Latinas expanded their technosocial analytical and computational thinking skills through a culturally responsive computing (CRC) curriculum (Scott et al., 2014). This ISL experience centered learners through intentional reflections, asset-building, in which mentor-teachers and graduate students built rapport and created safe spaces for learners to leverage their cultural experiences (assets) as part of the learning process, and connection, in which learners possessed a sense of community among their peers (Scott et al., 2014). Additionally, COMPUGIRLS researchers addressed power dynamics between themselves and participants by encouraging authentic inclusive collaboration through an interdisciplinary advisory board consisting of students, academics, community leaders, and school leaders. As demonstrated through the COMPUGIRLS example, ISL centers learners' authentic activities through culturally relevant activities, enhanced with either mentorship or caregiver participation (Barker et al., 2014; Cian et al., 2022; Morris et al., 2021).

Hussim et al. (2024) describe specific characteristics of ISL activities as being inquiry-based, problem- or project-based, design-based, cooperative learning, student-centered, hands-on, and 21st century skills-based, which cultivate youth's creativity, collaboration, communication, and critical thinking. Golegou et al. (2025) offer student-centered 21st century pedagogical approaches to STEM education, such as research-based, design thinking, brainstorming, and differentiated teaching. All these examples and characteristics are foundational to the informal learning experiences of STEM education. Just as learner-centered experiences, authentic activities, a culturally relevant curriculum, and hands-on or problem-based learning support meaningful engagement and persistence in STEM and computing, they are equally critical to building and supporting AI literacy.

AI Literacy

The AI-driven era marks a turning point in the public's interaction with AI, bringing systems that once operated largely behind the scenes into direct access with human dialog and interaction. As AI becomes increasingly embedded in instructional tools, tutoring software, learning management systems, web-based applications, and social media platforms, youth now engage with AI-generated information, companions, agents, etc., more frequently and intimately than ever before (Sidoti et al., 2025). Youth are increasingly embracing what was considered "too advanced for younger students" and applying this technology to their daily lives (Touretzky & Gardner-McCune, 2022, p.3).

In 2019, Touretzky et al. (2019) laid the foundation for AI education by developing AI4K12 guidelines to address the lack of age-appropriate AI curricula and standards in K-12 computer science education. This resulted in the development of the 5 Big Ideas in AI: 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 guidelines enabled nonexperts, such as youth, parents, and educators, to gain an understanding of the science and math behind AI to better engage and critically evaluate how AI technology was engineered to best support their needs and values (Long, et al. 2021a).

Touretzky et al. (2019) provided the foundation for what we now call AI literacy, "a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace" (Long and Magerko, p. 2, 2020). These competencies empower individuals to access, interpret, manipulate, and automate information efficiently. Long and Magerko (2020) suggest that digital, computational, scientific, and data literacies share overlapping competencies with AI literacy. These shared overlapping competencies lend to AI's interdisciplinary nature.

Ng et al. (2021) expand the definition of AI literacy to include the conceptual practice of educating learners with no prior knowledge. This lowers the barrier that is typically associated with computer science and other STEM disciplines, allowing youth to be met where they are academically. Furthermore, Chiu et al. (2024) "argues that the concepts of self-reflective mindsets should be included in the definition of AI literacy (i.e., AI competency), and practitioner perspectives should be taken into account for designing and developing K–12 AI education" (p. 2).

Veldhuis et al. (2025) note the importance of self-reflection by introducing critical AI literacy. The authors emphasized the "promot[ion of] youths' critical reflections on AI's societal, political, cultural, and ethical implications" (p. 12). Furthermore, Akgün et al. (2026) suggest that critical AI literacy adopts "community-centered approaches such as asset-based and humanizing mindset, centering cultural resources and funds of knowledge, and fostering a critical consciousness toward AI design and usage" (p.6). Both researchers' structures develop learners' critical capacity to recognize and understand the ways in which technology is not neutral and how to appropriately use it to gain the benefits of its promises (Casal-Otero et al., 2023). We can infer that the foundational skills that are necessary to build and support AI literacy are not solely technical knowledge or "AI Basics" but include self-reflection, critical evaluative skills, and interdisciplinary exploration (Casal-Otero et al., 2023).

RESEARCH METHOD

The ABCE Framework and AI Literacy Questionnaire was used to establish and compare baseline AI literacy across the three summer camp programs examined in our study. Using an explanatory sequential mixed-methods approach, our two-year research study examined participant responses to the questionnaire, semistructured individual interviews, and focus group interviews. Participants were youth from the TRAILS AI Camp, Create Tech, and CompSciConnect. Table 1 provides an overview of the participants, program design, learning environment, content, instructional design, informal STEM learning (ISL) practices, and instructor and youth actions for the three camps. While ISL practices were tailored to each camp, all camps implemented the Wendy Ward Hoffer (2012) Minds-on Math Workshop Model because of its effectiveness in engaging learners in conceptual understanding, challenging thinking, community centered learning, meaningful collaboration, accountable instructor-learner relationships, and near peer mentoring due to its mutual benefits to both the mentor and mentee.

Camp Program Overview

TRAILS AI Camp

The TRAILS AI Camp (TRAILS) is a three-week computing research program for high school youth. The youth who participated in this study had limited prior experience in coding and computing topics and little to no experience with AI concepts. In January 2024, through support from the Institute of Trustworthy AI in Law and Society, the TRAILS curriculum was overhauled to include a more balanced emphasis on the Touretzky et al. (2019) AI4K12 Big Idea #3: Learning - Computers can learn from data and Big Idea #5: Social Impacts - AI can impact society in both positive and negative ways.

The content was enhanced to be more youth-centered and focused on inquiry-based learning. It offered exploration activities and class discussions with datasets from real-world examples (e.g., Amazon's hiring algorithm) to deepen youth's understanding of the ethical implications of constructing AI systems that influence human behavior and lead to decisions that require transparency and fairness. This change further enhanced students' curiosity and provided a space for students to generate new ideas (Hussim et al., 2024).

Create Tech

The Create Tech camp (CT) is a two-week computing program for upper-middle school and high school youth. The youth who were part of this research study had "some to no prior experience in coding and computing topics, and who may be in the early stages of deciding whether to pursue the STEM field" (Avery, 2023). They had little to no prior experience with AI concepts. The CT curriculum consisted of both problem- and design-based learning in human-computer interaction and immersive media design concepts. Youth developed foundational skills in Python programming and Circuit Playground Express; applied their understanding, creativity, and design thinking skills to mini projects culminating in independent group projects addressing real-world problems of their choice; and utilized the university makerspace to personalize their wearable tech project by tinkering with materials (i.e., fabric, wood, metal), mechanical equipment (i.e., power tools, soldering iron), and technological equipment (i.e., 3D printer).

CompSciConnect

The CompSciConnect camp (CSC) is a three-year computing program for middle school youth, where each year they attend a two-week summer session and monthly sessions during the Fall and Spring semesters (Kramarczuk et al., 2023). The youth who were part of this research study were in the Terp group (CSC-Terp) – the third and final year of the program. The CSC-Terp curriculum focused on the "basics of object-oriented programming and creating virtual reality games using Unity or PlayCanvas and modular arithmetic" (Kramarczuk et al., 2023). As many of the youth had built apps and websites as part of their prior years in the CSC, they had intermediate computer science experience and possessed skills in "dynamic web design with an introduction to HTML, CSS, and JavaScript, octal and hexadecimal" (Kramarczuk et al., 2023). They had little to no prior experience with AI concepts.

Recruitment and Informed Consent

This study utilized convenience sampling by recruiting youth from the three computing summer camps. Only youth enrolled in the three summer programs were eligible to participate. Prior to the beginning of the program, youth and parents participated in an orientation that explained the curriculum, day-to-day logistics, and the research study. They were able to ask questions, opt out or give informed consent. Youth and parents who were unable to attend the orientation received the orientation meeting recording and a digital copy of the informed consent form through email. Paper copies were also available on the first day of the program, and a member of the research team was available to answer questions at morning drop-off and afternoon pick-up. Each parent or guardian was provided with an Adobe Sign link that would bring them to the consent form to read and sign electronically. Participation was communicated as being strictly voluntary. The signed consent forms were scanned or transferred to a secure, password-protected box drive. Additionally, throughout the recruitment process, all signed consent forms were tracked in a spreadsheet (stored in Box) to confirm which youth were eligible to participate.

Participant Demographics

After verifying informed consent and removing duplicate survey responses, there were 104 participants. Table 1 displays the participant demographic characteristics for each camp. Of the 104 total participants, there were 60 respondents from CSC-Terp, 25 from CT, and 19 from TRAILS. Most of the participants from the CSC-Terp group self-identified as girls/women (61.67%), Black or African Americans (35%), and were 13 years old (63.33%). Most of the participants from CT self-identified as boys/men (68.00%), Black or African American (40.00%), and were 14 years old (32.00%). Many of the participants from TRAILS self-identified as girls/women (47.37%) and Asians (63.16%) and were 16 years old (36.84%).

After confirming whether the participants had completed the informed consent and survey, 13 participants completed individual (n=8) and focus group interviews (n=5). Table 2 summarizes the demographic characteristics of the interview participants for each camp. Of the 13 total interviewees, there were six from CSC-Terp, four from CT, and three from TRAILS. Most interviewees self-identified as girls/women (61.54%) and were 14 years old (30.77%).

Table 1

Participant Demographic Characteristics

Demographic Characteristics	TRAILS		CSC-Terp		Create Tech	
	n	%	n	%	n	%
Total	19	18.10	60	57.14	25	23.81
Gender						
Boy/Man	8	42.11	21	35.00	17	68.00
Girl/Woman	9	47.37	37	61.67	7	28.00
Nonbinary /gender-fluid /third gender	0	0.00	1	1.67	1	4.00
Prefer not to say	2	10.53	0	0.00	0	0.00
Stanley Girly	0	0.00	1	1.67	0	0.00
Race and Ethnicity						
American Indian or Alaska Native	0	0.00	4	6.67	2	8.00
Asian	12	63.16	16	26.67	6	24.00
Black or African American	2	10.53	21	35.00	11	40.00
Hispanic or Latino/a/x/e or Spanish Origin	0	0.00	1	1.67	3	12.00
I prefer not to provide this information	2	10.53	3	5.00	2	8.00
Two or more races and/or ethnicities	0	0.00	7	11.67	2	8.00
White	3	15.79	8	13.33	0	0.00

Age						
12	0	0.00	11	18.33	0	0.00
13	0	0.00	38	63.33	7	28.00
14	5	26.32	9	15.00	8	32.00
15	6	31.58	2	3.33	3	12.00
16	7	36.84	0	0.00	4	16.00
17	1	5.26	0	0.00	3	12.00

Table 2

Semistructured Individual and Focus Group Interview Participant List

Participant	Camp	Gender	Age
Tiffany	TRAILS	Girl/Woman	16
Sacha	TRAILS	Girl/Woman	14
Brittney	CT	Girl/Woman	14
Bobby	CSC-Terp	Boy/Man	15
Simone	CSC-Terp	Girl/Woman	12
Erica	CSC-Terp	Girl/Woman	12
Danielle	CSC-Terp	Stanley Girl	13
Nicole	CT	Girl/Woman	13
Jordan	CSC-Terp	Boy/Man	12
Sarah	TRAILS	Girl/Woman	16
Mark	CT	Boy/Man	14
Lee	CT	Nonbinary/gender-fluid/third gender	17
Kim	CSC-Terp	Girl/Woman	14

Survey Questionnaire

The survey was conducted in Qualtrics, where all data was initially collected and later transferred to the Box Drive. The survey was available on the first day of each summer camp before formal camp learning began. The survey took no more than 15 minutes to complete. All youth were encouraged to complete the survey prior to starting to not single out any youth. However, only the youth with informed consent to participate in the study had their data saved and analyzed. Five years after the conclusion of this project, all data will be destroyed.

The survey had three parts: demographic questions, AI literacy questions, and ISL questions. In Appendix B, the questions and Likert scale statements are grouped into sections. In part one, the demographic questions included nine personally identifiable pieces of information (i.e., first and last name, email, age, gender, race, ethnicity, and camp name) to help the research team sort which survey responses to use as part of the research project and for further data analysis. Participants' names were replaced with a participant identification number. Before part two, youth were asked two open-ended questions: *"As a (fill in the blank, gender/race intersection), I believe that artificial intelligence impacts my life by… (fill in the blank)"* and *"When you hear 'AI tools' what do you think of?"*

In part two, the survey consisted of 32 statements derived from Ng et al.'s (2023) AI literacy questionnaire influenced by their ABCE framework and Touretzky et al.'s (2019) *Big Ideas #3: Learning - Computers can learn from data, and Big Idea #5: Societal Impacts - AI applications can impact society in both positive and negative ways*. We chose to include statements from Touretzky et al. (2019) Big Ideas to assess our learning outcomes for the AI camp curriculum. Of the 32 statements, seven statements represented the affective learning domain, one statement represented the behavioral learning domain, three statements represented the cognitive learning domain, and one statement represented the ethical learning domain. We added four statements from Big Idea #3 and thirteen statements from Big Idea #5. Finally, three statements were added that further explored AI literacy: knowledge, skills, and attitude. Youth were able to select their Likert scale response based on a 5-point scale, where the score of one meant strongly disagree to five strongly agree. In part three, there were four additional 5-point Likert scale statements and three open-ended questions from a previous internal informal STEM learning survey used to evaluate the youth's confidence, belonging, skills, persistence, and future plans in STEM.

Semistructured Interviews

In Appendix C, survey questions were used for the semistructured interviews (Lazar, 2017). On the last day of each camp, after all formal camp instruction and activities were concluded, a member of the research team went to each summer camp and recruited volunteers to participate in semistructured individual or focus group interviews. Convenience sampling was used. One camp's participants opted for a focus group interview. All interviews were recorded using Zoom, and a transcript was provided. Only one participant's interview was omitted from this analysis due to human error.

Participants were asked to introduce themselves by providing their name and pronouns. This information was collected for the purpose of pairing the interviewee with their previously assigned participant ID. This was to ensure that interviewees had a completed survey associated with their interview. The participants were asked three questions. The first question, "What do you remember about the survey since you took it at the beginning of camp (it's ok if you don't remember anything!)", and the last question, "The survey had you answer each of the questions on a scale of strongly agree to strongly disagree. Do you have other comments/thoughts that you would like to add that you couldn't share on the survey?" were about their survey experience. For the research study's analysis, only responses to the second question, consisting of eight statements selected from part two of the survey, were analyzed.

Data Analysis

Through a mixed-methods approach, we used an explanatory sequential design (QUAN → qual) (Creswell, 2022) to first examine 104 participant responses from three summer camp programs' AI Literacy Questionnaire. An interpretive phenomenological analysis examined semistructured individual interviews (n=8) and focus group interviews (n=5) with 13 participants to deepen our understanding of youth perceptions of AI.

Quantitative Analysis

The survey's Likert scale responses were assigned a numerical value of one to five, where one was assigned to strongly disagree, two were assigned to somewhat disagree, three were assigned to neither agree nor disagree, four were assigned to somewhat agree, and five were assigned to strongly agree. Using Ng et al.'s (2023) AI literacy questionnaire as a guide, the AI literacy statements were grouped into four ABCE framework dimensions: affective learning, behavioral learning, cognitive learning, and ethical learning. The ethical learning domain included statements influenced by Touretzky et al.'s (2019) Big Idea #5 guidelines. This decision was made because it aligns with our learning objectives for the TRAILS camp. A composite mean and standard deviation were calculated for each domain per camp (see Table 3). For further analysis of effect sizes, Cohen's *d* by way of Hedges' *g* and 95% confidence intervals were also calculated using Python (see Table 4).

Qualitative Analysis

An interpretive phenomenological analysis was conducted on the 13 interviews to better understand how youth view, personal experience, and interpret AI. Each interviewee's transcribed responses were placed into a spreadsheet, where responses were grouped by statement. Because responses were grouped by statement, a hybrid coding approach was used. The *a priori* codes that were based on the statements (e.g., jobs, decision-making, interaction, fairness, values, rules). After further analysis, inductive codes emerged such as conceptual knowledge, helper or assistant, societal impact, global considerations, accessibility, skepticism, bias, trust, ethics, and expectations. After all the response data were coded, we applied thematic analysis by grouping related codes together. Only three themes emerged, with at least six participants (46%) represented across themes.

Mixed Methods Analysis

The quantitative results were used to identify the effect size of each ABCE framework domain for comparing AI and non-AI camps responses. These results revealed areas with small or moderate-magnitude differences. Using the literature, we identify ISL practices that best support youth AI literacy. The qualitative results identified key themes and inferred areas where ISL practices could complement or challenge youth's perception of AI to support their AI literacy.

RESULTS

Quantitative Analysis

What is Youth's Baseline AI Literacy Prior to Starting Camp?

We administered the Ng et al. (2023) AI literacy questionnaire (AILQ) based on their ABCE framework. Appendix B shows which statements were grouped within each domain. By assigning a numerical value to the Likert scale response choices, we were able to calculate the composite mean and standard deviation, as shown in Table 3. We used the composite mean and standard deviation as our primary analysis. Because of the differences between composite means across camps per domain, we calculated Cohen's *d* using Hedges' *g* to explore these differences between TRAILS and non-AI camps (CT and CSC), as seen in Table 4, and explored patterns by item-level and demographic characteristics descriptively to contextualize domain-level findings.

Table 3

ABCE Framework Composite Mean and Standard Deviation by Program

Camp Name	CSC	CT	TRAILS	Overall Camp
Affective Learning	$\bar{X} = 3.79$ $\sigma = 1.07$	$\bar{X} = 4.17$ $\sigma = 0.94$	$\bar{X} = 4.26$ $\sigma = 0.72$	$\mu = 3.97$ $\sigma = 1.06$
Behavioral Learning	$\bar{X} = 3.58$ $\sigma = 1.21$	$\bar{X} = 4.40$ $\sigma = 0.96$	$\bar{X} = 4.47$ $\sigma = 0.51$	$\mu = 3.94$ $\sigma = 1.13$
Cognitive Learning	$\bar{X} = 3.96$ $\sigma = 1.04$	$\bar{X} = 4.05$ $\sigma = 0.83$	$\bar{X} = 4.04$ $\sigma = 1.00$	$\mu = 3.99$ $\sigma = 1.10$
Ethical Learning	$\bar{X} = 4.24$ $\sigma = 0.87$	$\bar{X} = 4.52$ $\sigma = 0.67$	$\bar{X} = 4.37$ $\sigma = 0.71$	$\mu = 4.33$ $\sigma = 0.88$

Table 4
ABCE Framework Effective Sizes for AI versus Non-AI Camps

Domain	Mean Diff (AI–NonAI)	Cohen's d (Hedges g)	95% CI
Affective Learning	0.29	0.29	[-0.21, 0.78]
Behavioral Learning	0.53	0.5	[0.00, 1.00]
Cognitive Learning	0.05	0.05	[-0.45, 0.54]
Ethical Learning	0.04	0.05	[-0.45, 0.54]

Affective Learning

Youth from TRAILS showed a higher composite mean score (M=4.26, SD=0.72) than non-AI camps. The effect size (ES=0.29) results indicate a small magnitude difference toward youth's "interests, confidence, motivation, attitudes and self-efficacy" in AI (Ng et al., 2023, p.1086). In exploring item-level patterns to contextualize this domain, when compared to non-AI camp youth, TRAILS youth responses to CL01 and CL04 survey statements had lower mean scores of 3.58 (SD 1.12) and 3.84 (SD 0.62), respectively. This was a notable finding because it suggests that most TRAILS youth self-reported less confidence in their ability to learn basic concepts about AI and understand AI resources/tools prior to starting camp.

Behavioral Learning

Youth from TRAILS showed a higher composite mean score (M=4.47, SD=0.51) than non-AI camps. The effect size (ES=0.5) results indicate a moderate magnitude difference toward youth keeping updated with the latest AI technologies. This finding suggests that TRAILS youth more strongly exhibited a "positive learning behavior" toward AI than youth in non-AI camps (Ng et al., 2023, p. 1086). Because there was only one item in this domain, we conducted descriptive analysis based on age and gender to contextualize this domain. We found that the composite means for youth aged 14-17 were above the overall mean score of 3.94 (SD=1.13). This finding purports that as youth age, their behavioral learning becomes more positive. This supports TRAILS's higher composite mean score, as the youth participating in this camp fall within this age range. The composite means by gender resulted in youth, who identify as girls/women, have a lower mean score 3.85 (SD=1.09) with a negatively skewed distribution. This finding suggests that most youth, who identify as girls/women, agreed or strongly agreed with the statement and self-reported a high behavior learning score prior to starting camp.

Cognitive Learning

Youth from TRAILS (M=4.04, SD=1.00) and CT (M=4.05, SD=0.83) showed comparable composite mean scores. The effect size (ES=0.05) results indicate a small magnitude difference between youth from AI and non-AI camps, meaning there was minimal differentiation toward youth's self-reported knowledge and skills in AI across camps (Ng et al., 2023). In exploring item-level patterns to contextualize this domain, across all camps, youth responses to the EC03 survey statement had lower mean scores (TRAILS M=3.42, SD=1.12; CT M=3.68, SD=1.18; CSC-Terp M=3.25, SD=1.27). This finding suggests that most youth self-reported less confidence in their ability to create AI-driven solutions (e.g., chatbots, robotics) prior to starting camp.

Ethical Learning

Across all camps, the composite mean scores were consistently high (CT M=4.52, SD=0.67; TRAILS M=4.37, SD=0.71; and CSC M=4.24, SD=0.87). The effect size (ES=0.04) results indicate a small magnitude difference, meaning there was minimal differentiation among youth's perception of AI's social responsibility, ethical use, fairness, privacy, and security (Ng et al., 2023). In exploring item-level patterns to contextualize this domain, the responses to the statement, "AI systems do not act in ways that violate people's privacy rights," showed the lowest mean scores across all camps. Further descriptive statistical analysis resulted in both non-AI camps producing negatively skewed distribution results, suggesting that most non-AI youth strongly agree with this statement. The descriptive statistical analysis for TRAILS resulted in a normal distribution, suggesting that TRAILS youth had varying responses.

Overall affective, cognitive, and ethical learning domain effect sizes indicated small magnitude differences between AI and non-AI camps. This suggests a similar baseline AI literacy within these domains among youth participating in these camps. The behavioral learning domain effect size indicated moderate magnitude differences between AI and non-AI camps. This suggests that youth participating in an AI-focused camp are more likely to demonstrate positive learning behavior toward AI. We recommend conducting descriptive statistical analysis by item-level, gender, age, and other demographic characteristics to contextualize the data. The results from this AILQ survey inform which ISL experiences would be most useful within the behavioral learning domain while leveraging youth's self-reported strengths from other domains

Qualitative Analysis

What is Youth's Perception of AI Technology and Systems after Completing Camp?

An interpretive phenomenological analysis was conducted to deepen our understanding of youth's personal perception and views of AI in their individual lives (Smith et al., 1999). We identified three key themes where at least six (46%) unique participants were represented per theme: AI's impact on the workplace; trustworthiness and ethical AI; and regulating AI.

AI's Impact on the Workplace

Most of the youth (62%) who were interviewed expressed opinions about AI presence within the workplace. There were concerns about the integration of AI within the workplace, resulting in job displacement and erasure. Sacha, Sarah, Erica, Mark, Simone, and Lee acknowledge this concern in their responses by using terms and phrases such as "job displacement", "loss of jobs", "taking over control of their jobs", "robots are taking the jobs people might need", "jobs are obsolete", and "changes the way humans create", respectively, with Sacha emphasizing that this phenomenon is a "really big debate."

Youth provided personal examples of this phenomenon, where they described how AI was shifting their parents' workplace through their personal experiences. Simone shares her mom's experience with AI:

> "Like, my mom was saying at her job, like a lot of, like, stuff that they use, like, they have like computers and AI is like helping, like take over like people's positions and stuff. So yeah, I feel like it is taking over jobs." (Simone)

Mark shares about his dad's experience with AI:

> "Well, before I was talking about this with my dad by the way, he used to go to the office and review papers because he's an attorney. But now AI does all of that. So he just has to supervise it. So it makes his life so much easier. But it's a part of the workforce now." (Mark)

In Simone and Mark's responses, they recognize AI's usefulness considering their concerns that AI is taking over tasks and people's positions within their parent's workplace. By describing AI attributes such as helper, needing to be supervised, and part of the workforce, youth acknowledge that AI's impact in the workplace could be positive if monitored by a human being.

However, there remains caution and concern with each positive attribute. For example, here is an exchange that occurred within our focus group between Danielle, Erica, and Simone. Here, Danielle shares her personal experience with AI at a local restaurant:

> "Yes. This is random, but like, at Denny's, they have like a robot that brings you your food. So like, you don't need to have, like, waitresses bringing out the food, you certainly [don't] have to carry everything. So that's kind of helpful." (Danielle)
>
> "But people also lose their jobs from robots and technology taking over control of their jobs. So now people need more jobs and robots are taking the jobs people might need to pay for food…and a house..." (Erica)

> “And we were saying that basically, AI, it can take over one person's job. So it helps, like, making business move quicker. And, like, if they're serving people food, it can be more beneficial and easier. But at the end, you don't have to, like pay for it. I mean, like, you have to pay them to do the job. But at the same time, people are losing jobs and like, yeah.” (Simone)

This exchange shows the duality that AI possesses within the minds of youth. The youth in this exchange acknowledge AI’s duality as both helpful and harmful.

The findings within this key theme suggest that youth’s personal view of AI in the workplace is one of potential job displacements and erasure. Our youth’s responses suggest that when AI is a helper, it should be supervised and part of the workforce. They suggest that this approach may lead to positive outcomes such as making business operations more efficient, contributing to work becoming easier, or being completed quickly.

Trustworthiness and Ethical AI

Over a third of the youth (46%) who were interviewed discussed trust, fairness, morality, and ethical discernment within their responses about AI. Youth stressed that when AI is used to make decisions about humans, there should be a human involved in the process. For example, when AI is being used to achieve a level of ethical or moral actions, Tiffany states:

> “Because [AI is] not, like, ethically and morally like people, humans should look out for each other. And if you are going to put your trust into AI. You should, like, at least have, like some sort of, like, human, like, you should morally feel like computers should do, for like, benefiting everyone.” (Tiffany)

In her response, Tiffany acknowledges that AI is not a person and does not possess ethical and moral attributes like people. She suggests that morally, humans who trust AI should look out for other humans and be directly involved with computers used for ethical or moral actions. Brittney's response complements Tiffany’s response by emphasizing human agency to speak up and share their ideas. Brittney states:

> “A lot of times it's more of, like, a choice decided on ethics most of the time, like computers can't really decide what's ethical or not. So it's important to have humans also have a chance to speak and show their ideas.” (Brittney)

Through this phenomenon, youth responses highlight an interdependent relationship between AI and humans. This suggests that AI’s trustworthiness, fairness, and ethical discernment depend on humans’ capacity to possess and implement these attributes. Also, youth responses underscore the preservation of human agency and moral judgment in AI

Additionally, Sarah and Lee's responses both address the bias and unethical use of training data used to create and train AI. Sarah suggests that training data should be representative of the people it was intended for, to thoroughly check for implicit bias, and she ends with a caution to "not repeat history."

These findings suggest that a key theme that emerges in youth's personal view of AI consists of trust, fairness, and moral and ethical discernment. Our youth's responses suggest that humans trusting AI to make decisions or using AI as a tool for decision-making should thoroughly evaluate the data used to create and train AI for implicit bias and ensure that it is representative of the people it is intended for. Additionally, human involvement and agency are essential to providing the human touch that AI lacks.

Regulating AI

Nearly half of the youth (46%) who were interviewed suggested that AI should have defined regulations and limitations. For example, in Sacha's response, she stressed the danger of AI if it lacked necessary rules and limitations. Simone and Lee used examples of AI use within law enforcement and the medical fields to emphasize the danger that unregulated AI could bring in these industries. For example, Simone reflects on a conversation with her mom:

> "You don't want to tell AI something that could, like, be personal, because my mom was, she was saying like, just like this thing where, like, for doctors are for AI. They help, like, the appointment, like, instead of a doctor take down notes and stuff, the AI does it. So this is also personal information about a person. So I feel like there needs to be rules. Like, oh no you don't just go to this, to the FBI or whatever." (Simone)

Simone's response suggests that rules should be enforced when AI is being used to support doctors with medical record keeping. Her response underscores concern with personal data privacy due to the level of sensitivity surrounding the data. In addition, Lee shares that AI should not be used in military and law enforcement operations. They stated:

> "I feel like artificial intelligence shouldn't have too big of a part in military operations because I feel like that could lead to somewhere bad or even police operations enforcement. I feel that AI, to keep people safe, there are just some things that AI shouldn't be able to do. Shouldn't be a part of so, so, interpreting that as protecting people from AI. (Lee)

Lee's response highlights her concern for personal safety. She suggests that keeping people safe means not using AI in military and law enforcement operations regardless of rules and limitations. Additionally, Tiffany and Kim provide scenarios in their responses, where a human can experience harm at the expense of an AI mistake if consequences for AI are not in place. Here, Tiffany describes humans reaping consequences for AI's mistakes in law enforcement or the workplace:

> “I've seen that AI, like when it comes to generative AI, there can be, like, it can cause a bit of trouble. Like, when it comes to, like law enforcement or workplaces. Because if something goes wrong, then like, and it's, it's AI's fault, and like you can't blame it on a human. It's the AI's fault. And someone, something happens to that person like, there's not much you can do. It's like, it's, it's not their fault. (Tiffany)

This response suggests that human harm is doubled because of the initial harm caused by AI mistakes and harm due to AI impunity.

Here, Kim describes AI reaping consequences for mistakes that harm society:

> “I feel like AI can get away with a lot of stuff thinking like if they were self-conscious or like helping, they can get away with a lot of things. If, say, the AI hurt somebody, just like the dog or somebody, the AI needs to be put to rest, like, it needs to. The plug needs to be taken out, because that's not fair to the community, because it's not fair to all the dogs or stuff like that, that have hurt people and had to get put down. (Kim)

Kim uses a vivid analogy of a dog that makes a mistake that harms a person and is later put down. This analogy conveys the level of consequence she feels is acceptable for AI, which is to pull the plug.

The findings within this key theme suggest that youth’s personal view of AI consists of regulating or limiting AI. Our youth responses suggest that personal data privacy and safety should be prioritized when establishing regulations and limitations for AI in law enforcement, military, and medical operations. Youth’s responses highlight concerns for humans receiving consequences caused by AI mistakes and insist that AI should have clearly defined consequences that appropriately match the level of harm caused to the human and/or community.

DISCUSSION & CONCLUSIONS

How Can Youth’s Baseline AI Literacy and Perceptions of AI Technology and Systems Inform What Informal STEM Learning Practices Support Youth’s AI Literacy?

The results from the quantitative and qualitative analysis suggest that youth across camps are developing their worldview of AI prior to entering camp. We infer that it is their worldview that inspires their participation or resistance. The results of the behavior learning domain illustrate that youth participating in TRAILS self-reported positive learning behavior compared to youth in non-AI camps. Because ISL offers youth-centered cooperative learning activities, it would support youth AI literacy.

Many youth across camps had little to no difference in the affective, cognitive, and ethical learning domains. Youth shared similarities in their understanding, skills, and ethical discernment toward AI. This suggests that learning opportunities that include youth's prior knowledge and understanding of basic skills and resources/tools in AI, AI-driven solutions, and discourse on topics related to AI's effect on people's privacy would support youth AI literacy. ISL practices, such as activities that increase technology fluency, project-based curriculum, and mentorship (e.g., near peer, caregiver, community, or industry), support youth AI literacy.

In this study, our youth's perception of AI technology and systems included regulating or limited AI; human engagement and agency with AI; strictly regulated or limited industry use of AI (e.g., law enforcement, military, and medical operations examples); and AI's interdependent relationship with society's fair, trustworthy, and ethical discernment. These assumptions were based on their primary (e.g., Denny's restaurant example) and secondary (e.g., parents' interaction with AI in the workplace examples) experiences. ISL offers youth culturally relevant authentic activities where their personal lived experiences help shape youth's AI literacy.

As a result of this study, our research team developed a new practice called informal AI learning (I-AIL). We define I-AIL as a pedagogical practice that posits learners as codesigners and cocreators of their AI knowledge. By prioritizing culturally relevant, mind-on and hands-on learning, I-AIL is iterative and intentionally grounded in learners' interests, curiosity, and critical awareness of self, society. It takes into consideration that youth possess worldviews about AI technology and systems prior to formal AI instruction. Whether as a discipline or as a tool, I-AIL encourages youth to develop technology fluency, AI *plus* identity, self-efficacy and persistence in AI, and meaningful reflection and action toward social, economic, political, and environmental impacts of AI within their lives and communities. Additionally, I-AIL encourages youth to challenge and question the usage of AI technology and systems. This practice is further enhanced by the inclusion of peer-to-peer interaction, near-peer mentorship, caregiver engagement, and community-based partnerships. Although this practice targets youth learners, the attributes of this practice can be tailored to adult learners.

STEM and computing education researchers sense the urgency of supporting youth's development of AI literacy. Although there are AI literacy frameworks that guide research and instructional practices, there have been very few empirical baseline data that provide insight into youth, 12-17 years old, AI literacy prior to participating in an ISL experience, such as a summer camp. Through our investigation we have baseline data, deepened our understanding of youth's perception of AI technology and systems, and identified ISL practices to best support youth AI literacy in our next iteration of our camps. Our future work includes investigating the causal relationship between ISL practices and youth AI literacy, exploring how youth's information seeking behavior influences their baseline AI literacy, and deepening our understanding of how youth's worldview shapes their adoption or resistance to AI technology and systems.

We acknowledge that codesigning a model for I-AIL needs interdisciplinary participation not only from STEM and computer science education researchers and practitioners. We also recognize that conducting this study was limited by the location, timeframe, and content of the summer camp. Due to our limited control over content and instructor training, participants' interviews may have been impacted by these variables. Future researchers should consider controlling more variables throughout the life cycle of the study to ensure more reliability and validity of the results.

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AI USE DISCLOSURE STATEMENT

The author used generative AI tools (ChatGPT, OpenAI, and Grammarly) to assist with light editing, formatting, and Python code generation during the initial draft of the manuscript. All research content, data analysis, conclusions drawn, ideas, interpretations, and findings are the original work of the author. Generative AI tools were not used in the final edits and preparation of the manuscript for publication.

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Appendix A

Camp Program Overview

Characteristics	Computer Science	Wearable Tech	AI Research
Participants	Rising 8th-9th graders; prior computing experience	Rising 8th-12th graders; none to some prior computing experience	Rising 9th-12th graders; none to some prior computing experience
Program Design	3-years; 2-week summer camp and monthly meetings Fall/Spring; peer and family showcases Fall; peer and community showcase Spring; community building activities;	2-weeks summer camp; separate sessions for middle and high school youth; end-of-camp peer-to-peer showcase; community building activities; field trips;	3-weeks in the summer; 1-week of asynchronous learning and 2 weeks of in-person synchronous learning; end-of-camp peer and family showcase;

	field trips; faculty/postdoc guest speakers; lab tours and demos	faculty/postdoc guest speakers;	community building activities; field trips; faculty/postdoc guest speakers;
Learning Environment	University classroom with round tables for collaboration, and VR studio to demo 3D game design projects	University classroom with round tables for collaboration, and university makerspace	University classroom with round tables for collaboration and university huddle rooms for small group collaboration
Content	3D Game Design for VR environments, Foundational JavaScript programming skills, Geometry and Physics	Human-computer interaction and immersive media design concepts, Foundational Python programming skills, and Circuit Playground Express	Foundational Python programming skills, data manipulation, algorithms, and visualizations
Instructional Design	Minds-on Math Workshop Model; Community of Learners; near peer mentors; UDL; coteacher model; CS Pedagogy; Culturally Responsive Pedagogy	Minds-on Math Workshop Model; Project-based learning; near peer mentors; UDL; coteacher model; CS Pedagogy; Culturally Responsive Pedagogy	Minds-on Math Workshop Model; Project-based learning; Big Idea #3 and #5; Near peer mentors, Culturally Responsive Pedagogy; Scientific Method Pedagogy
Informal STEM Learning Practices	Design-based project, cooperative learning, student-centered, hands-on, 21st century skills	Problem-based and design-based project, cooperative learning, student-centered, hands-on, 21st century skills	Inquiry-based project, cooperative learning, student-centered, hands-on, 21st century skills
Instructor Actions	Directed instruction, mini-lessons, guided practice; facilitate independent practice and design-based learning; reward behavior; supervision; community building & social activities	Directed instruction, mini-lessons, guided practice; facilitate independent practice and problem-based and design-based learning; makerspace; reward behavior; supervision;	Directed instruction; facilitate inquiry-based learning; mentorship through near peer and postdoc/faculty

		community building & social activities	
Youth Actions	Create group norms; Collaborate with peers to create a 3D game project using geometry, physic, and design concepts; develop leadership and presentation skills	Create group norms; develop problem-solving and design thinking skills; collaborate with peers to create a wearable technology prototype to address a real-world problem; develop leadership and presentation skills	Participate in asynchronous and in-person learning; Select research project; Collaborate with project group; present findings at the end of camp; develop leadership and presentation skills

Appendix B

AI Literacy Survey Questions

Demographic Question	DE01 What is your first name? DE02 What is your last name? DE03 What is your email? (If you don't have an email, please write your parent/guardian's email) DE04 Which Summer Academy are you participating in? DE05 How old are you? DE06 As a (fill in the blank, gender/race intersection), I believe that artificial intelligence impacts my life by… (fill in the blank) DE06 Which of the following ethnic or racial categories best describes how you self-identify? DE07 What is your ethnicity? DE08 Which gender(s) do you identify with? (Choose all that apply)
Affective Learning	IM01 Given who I am, I believe artificial intelligence (AI) is relevant to my everyday life (e.g., personal, school). IM02 Learning AI is interesting. IM04 I am curious about discovering new AI technologies. CL01 I can understand AI resources/tools. CL04 I am confident I can learn basic concepts about AI. CI02 modified I believe that being able to use AI is a relevant skill for all jobs, not just coding jobs. CI04 My future career will involve AI.
Behavioral Learning	BI02 I must keep myself updated with the latest AI technologies.
Cognitive Learning	KU01 I know what AI is and recall the definitions of AI. KU02-i I know how to use AI tools (e.g., Siri, chatbot). EC03 I can create AI-driven solutions (e.g., chatbots, robotics).
Ethical Learning	AIE13 People who use AI tools should understand the purpose of the AI system, how it works, and its limitations.

Big Idea #3: Learning	3-A-i Computers learn differently than people. Converse of 3-A-i Both people and computers learn the same way. 3-A-ii How well a computer learns to classify depends on the data people use to train it. 3-C-i People decide which features to include in a dataset and how to encode them in a computer.
Big Idea 5: Societal Impact	5-A-i The decisions made when developing an AI system can impact different people and communities in different ways. 5-A-i Computers can make decisions that work for most people but harm or disadvantage other people. 5-A-i Different groups of people may be affected differently by AI systems. 5-A-i AI can be used to help disadvantaged people. 5-A-ii Creators of AI systems should make sure that their systems treat everyone fairly. 5-A-ii AI systems do not act in ways that violate people's privacy rights. 5-A-iii AI developers need to understand that values vary across cultures and ensure these values inform the design of the products they create. 5-B-i AI is changing daily life as intelligent machines find new roles in society. 5-B-ii It is okay to make rules for AI in places where we need to protect society. 5-C-i Society has undergone changes because of AI, and these changes will continue in the future. 5-C-ii As AI and robotic technologies are adopted in the workplace, the ways people perform their jobs will change. 5-D-i AI tools are becoming freely available and can be used by people without advanced degrees (Bachelors, Masters, Doctorate, etc.) or expensive equipment. 5-D-ii AI systems should be designed to benefit people.
Literacy	AIE13 I can use generative AI software (ChatGPT, Gemini, Midjourney, etc.) AIC05 I will use AI-related problem-solving skills on future tasks. AIP05 I am confident that I can use AI tools.
Informal STEM Learning	EV01 What do you plan to do when you graduate from high school? Check all that apply. EV02 What do you hope to pursue in the future? (Provide an answer for every statement) EV03 Are you planning to apply to the university for college? EV04 I think I can succeed in a science, technology, engineering, or

	mathematics (STEM) field. EV05 I will be treated fairly in a STEM job. EV06 I expect to be given the same opportunities for pay raises and promotions as my fellow workers if I enter a STEM field. EV07 I am confident in my ability to develop programming skills.

Appendix C

AI Literacy Semistructured Interview Questions

Category	Question
Demographic Question	DE01 What is your first name? DE02 What is your last name? DE09 What are your pronouns?
Opening Question	What do you remember about the survey since you took it at the beginning of camp (it's ok if you don't remember anything!)
Affective Learning	IM01 Given who I am, I believe artificial intelligence (AI) is relevant to my everyday life (e.g., personal, school).
Big Idea #3: Learning	3-A-i Computers learn differently than people. 3-A-ii How well a computer learns to classify depends on the data people use to train it.
Big Idea 5: Societal Impact	5-A-i The decisions made when developing an AI system can impact different people and communities in different ways. 5-A-i Computers can make decisions that work for most people but harm or disadvantage other people. 5-A-ii Creators of AI systems should make sure that their systems treat everyone fairly. 5-A-iii AI developers need to understand that values vary across cultures and ensure these values inform the design of the products they create. 5-B-ii It is okay to make rules for AI in places where we need to protect society. 5-C-ii As AI and robotic technologies are adopted in the workplace, the ways people perform their jobs will change.
Informal STEM Learning	EV06 I expect to be given the same opportunities for pay raises and promotions as my fellow workers if I enter a STEM field.
Closing Question	The survey had you answer each of the questions on a scale of strongly agree to strongly disagree. Do you have other comments/thoughts that you would like to add that you couldn't share on the survey?

Bio

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