A Constructivist Approach to Structuring Technical and Socio-Ethical AI Literacy Lessons

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ABSTRACT

With the increasing usage of Large Language Models like ChatGPT by teenagers, it's important to teach students about how these models work and the impacts these models have on society. Existing AI literacy efforts showcase a wide range of frameworks and implementations, which makes it challenging for educators to compare, select, and apply to their own lesson designs. In this experience report, we extend the constructivist framework, Evocation-Realization-Reflection (ERR), to design a general lesson structure for AI literacy and demonstrate how this structure can provide coherence across individual lessons, supporting student learning, application, and reflection. We illustrate this structure's effectiveness through two model lessons and show how it enhanced student engagement and understanding. Finally, we discuss implications for educators interested in adopting this framework in diverse learning contexts.

CCS CONCEPTS

• **Applied computing → Education**; • **Social and professional topics → K-12 education**; **Computing literacy**.

KEYWORDS

AI literacy, AI in K-12, Constructivism, lesson design, anchored activities, large language models

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1 INTRODUCTION

Many high school students are active users of large language model (LLM) based technologies like ChatGPT [27]. In a 2024 global survey, 86% of students reported regularly using AI [6]. Despite the widespread use of LLM-based tools, 58% of students do not feel they have sufficient AI knowledge and skills [6]. As such, AI literacy and particularly LLM-based literacy is important in preparing students to be critical, responsible, and empowered users of these tools.

Since many existing AI literacy lessons were independently developed for specific audiences, there lacks a consistent pedagogical framework across different AI literacy lessons for educators to use when integrating both the technical and socio-ethical dimensions of AI literacy into their classrooms. Existing AI literacy lessons and curricula often only address either the technical dimension or the socio-ethical dimension of AI literacy [10, 14, 19, 33, 34, 45]. In other computing domains, prior work has demonstrated the importance of providing students both dimensions [42, 44].

In our work, we design a general lesson structure applicable for AI literacy lessons, by extending the constructivist framework of Evocation-Realization-Reflection (ERR). The ERR framework supports students in activating their prior knowledge and integrating new knowledge into existing mental models [11]. In the context of teaching AI literacy, where students might have a lot of informal exposure and experiences with LLM-based tools like ChatGPT, the ERR framework facilitates students in critically examining their prior experiences and mental models related to LLMs (Evocation), engage in guided experimentation with LLMs to deepen their conceptual understanding (Realization of Meaning), and then reflect on what they learned to generalize to other contexts (Reflection).

The structure consists of 7 components: (1) pre-lesson activity, (2) pre-lesson activity debrief, (3) pre-lesson knowledge check, (4) Instructor-led content with elements of active learning, (5) post-lesson knowledge check, (6) post-lesson activity, and (7) post-lesson activity debrief. The activities are designed based on anchored learning through situating the lesson content into a real-world context that students learn from. We use a custom web-interface to facilitate the anchored activities and an interactive polling platform to support activity debriefs and knowledge checks.

To test the adequacy and effectiveness of the lesson structure, we applied it to lessons in a 3-week AI literacy curriculum offered to 30 high school students in Summer 2025. Featuring two model lessons, we show that the ERR framework and anchored activities effectively supported student learning, application, and reflection. For instance, anchored activities were effective in surfacing students' prior knowledge and experiences with LLMs and helped educators identify potential misconceptions. Furthermore, all students reported that the anchored activities supported their learning by helping them apply course materials.

2 RELATED WORK

2.1 Existing Efforts in AI Literacy

AI literacy seeks to equip people with the skills to use, create, and critique AI systems [22, 38]. Existing work in AI literacy has developed formal curricula, individual lessons, and tools for K-12 educators to integrate into their classrooms [7, 14, 26, 33, 44]. Some have developed AI literacy lessons to cover specific topics, such as machine learning, machine learning data practices, bias, ethics, auditing, [24, 25, 32, 33, 35].

Recently, Zhang et al. [44] define the core dimensions of AI literacy as *technical*, *socio-ethical*, and *career futures*. For the technical dimension, many existing lessons use tool-based experiences to help students understand topics like robotics, gesture recognition, and clustering through hands-on-experiences, but lack explicit guidelines on how these tools can be integrated into specific lessons [13, 17, 41]. On the other hand, socio-ethical lessons often leverage different pedagogical frameworks such as "critical pedagogy" and "funds of knowledge" to support student learning [8, 31]. Because technical and socio-ethical AI literacy lessons are structured differently—emphasizing distinct strengths (e.g., tool use and pedagogical frameworks)—educators may face challenges trying to integrate both approaches into their classrooms. To address this challenge, we apply the pedagogical framework of Evocation-Realization-Reflection (Section 2.2) to AI literacy lessons across the core dimensions and integrate tools as part of the framework.

2.2 Evocation-Realization-Reflection (ERR) Framework

Yaghobová et. al. applied the constructivist educational framework of Evocation-Realization-Reflection (ERR) to teaching students about the internet to help students construct new mental models by identifying, correcting, and extending their existing knowledge [2, 43]. Within AI literacy, many students form their mental models for what AI is and how it works through exposure to media and personal usage [12, 16, 36]. For educators, it is important to understand students' prior knowledge and possible misconceptions of a topic in order to correct incomplete mental models [9].

The ERR framework focuses on three main phases: (1) **Evocation** where students' prior knowledge and preconceptions are surfaced through activities, (2) **Realization of Meaning** where new information is introduced through teacher-led instruction and interactive activities, and (3) **Reflection** where students integrate new knowledge into their existing mental models through reflection-based activities [23]. By using the ERR framework, we provide structured lesson outlines and activities that help surface students' prior knowledge and facilitate reflection and knowledge consolidation. Structuring the curriculum around the ERR framework allows for a streamlined approach to integrating new lessons in AI literacy.

2.3 Anchored Activities

Anchored learning posits that learning is established through active participation in the world [3], and uses real-world problem solving environments to motivate and teach concepts to students [5, 40]. In the context of computing education, anchored instruction has been used in the context of teaching elementary school students algorithmic thinking concepts [21]. Since students often use chat-based LLMs like ChatGPT, we use "anchored activities" to refer to common tasks that high school students use LLMs for, such as summarization, question answering, and drafting [29]. Educators can provide students with anchored activities that connect course material to students' existing experiences with LLMs.

3 AI LITERACY LESSONS

We present the design our AI literacy lessons by first defining core components: anchored activities, activity debriefs, knowledge checks, and instructor-led content (Section 3.1). We then organize these components into a seven-step lesson structure aligned with the three stages of the ERR framework (Section 3.2). We describe two supporting tools that facilitate this lesson structure: a custom web interface and an interactive polling platform (Section 3.3). Lastly, we present our data collection and analysis methods (Section 3.4).

3.1 Lesson Components

We designed the four core components of AI literacy lessons—anchored activities, activity debriefs, knowledge checks, and instructor-led content—with the following intentions.

Anchored activities help students situate the instruction within meaningful problem solving environments. We conceptualize these environments along two dimensions: the task and context. For the task, we focus on common student uses of LLMs: summarization, brainstorming, and drafting. For the context, we consider specific scenarios where these tasks could take place. For example, a summarization task might use the introduction section of the seminal "Attention is All You Need" paper as its context [39]. Anchored activities were administered via a custom web-interface that provides an all-in-one platform for the student to view the activity description, access an LLM-based chatbot, and draft their submission.

Activity debriefs help students think about and reflect on the strategies and steps they used to complete an anchored activity. Activity debriefs were structured in two steps: (1) individual student reflection, and (2) class-wide discussion. Students submit individual reflections on an interactive polling platform, which allows them to view responses from their classmates. Individual student reflections then serve as the starting point for the class-wide discussion.

Knowledge checks gauge students' prior knowledge before the lesson and assess their learning after a lesson. To keep them low-stakes and integrated into the lesson, they are delivered through an interactive polling platform.

Instructor-led content is the main instructional section of the lesson. The instructor uses lecture slides and anchored learning activities (e.g., think-pair-share [18], class-wide discussion [30]).

3.2 Lesson Structure (ERR Framework)

The lesson structure corresponds to the three stages of the ERR framework and consists of 7 steps: (1) pre-lesson anchored activity, (2) pre-lesson activity debrief, (3) pre-lesson knowledge check, (4) instructor-led content with anchored activities, (5) post-lesson knowledge check, (6) post-lesson activity, (7) post-lesson debrief (Figure 1).

The lesson structure uses repeated exposure to the same anchored activity task and debrief both before and after the lesson (with possible changes in activity context). The pre-lesson activity reveals students' implicit behavior when completing the activity. The post-lesson task allows students to apply what they learned in the lesson to the same task. Paired with the the debriefs after each activity, the lesson structure facilitates both student application of lesson content and self-reflection to surface behavior patterns.

The lesson structure also utilizes repeated low-stakes knowledge checks before the lesson to help educators assess possible student misconceptions and after the lesson to provide immediate feedback on lesson concepts that might cause confusion. Additionally, knowledge checks are designed to provide students an opportunity to recognize their own progress.

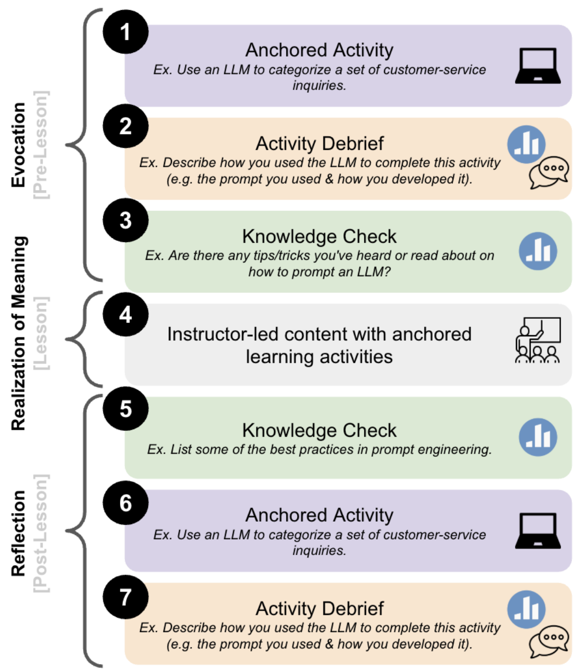

Figure 1: ERR framework applied to the Prompt Engineering Lesson (L1-Prompt). For visualization purposes, we only display one of the pre- and post-lesson activities as an example. We provide a more detailed description of the design of the model lessons in Section 4.1

3.3 Tools

To help facilitate the anchored activities and debriefs, we use two tools to support the learning and teaching process: a custom-web interface and an interactive polling platform.

Custom Web-Interface (Chatbot). To support the anchored activities, we designed a custom web-interface that provides students an all-in-one platform to complete the anchored activities. Our interface provided students access to the activity description, a chat-based LLM, and a text-editor where students wrote their submission (Figure 2). We provided students access to the LLMs they reported using most frequently (OpenAI's GPT-4o, Meta's Llama-3.1-405B, and Deepseek's R1), a set of parameter controls (e.g. temperature, top_p, and max_tokens), a system prompt, and a chat-based interface for the student to prompt the LLM.

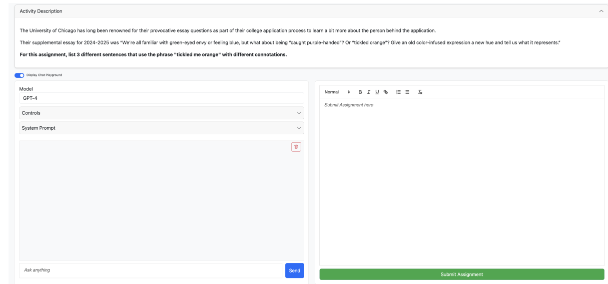

Figure 2: Custom activity interface that provides students access to different LLMs, a set of parameter controls, a system prompt, and a chat interface.

Interactive Polling Platform (PollEv). To help facilitate individual student reflections and group discussions, we used PollEverywhere (PollEv),[1] an interactive polling platform. PollEv allows the instructor to display student responses, administer time-constraints on certain questions, and track student participation across the lesson. PollEv also integrates directly into Google Slides.

3.4 Data Collection and Analysis

To assess student learning, we used qualitative data from the pre- and post-lesson activity debriefs (PollEv) and knowledge checks (PollEv) [4]. To understand student experiences in the course, we analyzed qualitative data from four sources: **classroom observations**, **lesson exit tickets**, **weekly course evaluations**, **post-course evaluations**. Classroom observations were conducted by trained TAs. Lesson exit tickets were completed after each lesson to facilitate student reflection on their understanding of LLMs and on concepts they might be confused about. Weekly Evaluations were used to collect student feedback on the course materials, structure, and activities. Post-Course Evaluations occurred on the last day of class and collected students' overall experiences with the class and lesson components.

4 CLASSROOM CONTEXT

We implemented the ERR framework to a majority of the lessons within a 3-week AI literacy curriculum that covered the technical, socio-ethical, and career future dimensions of AI literacy. This course was offered through an R1 institution's immersive, 3-week high school Pre-College program during Summer 2025. Classes were held weekdays from 9am-3pm with an 1.5 hour lunch break (75 instructional hours total). Students received a letter grade and college credit. This study was approved by our institutional IRB.

The instructor was the first author who designed, taught, and implemented the ERR framework to the lessons in the course. They were a PhD student at the R1 institution with a research background in Human-AI Interaction. The instructor was supported by two TAs who conducted classroom observations and graded student work.

There were 30 students in the class. 18 students consented to participate in the research study. Based on the pre-course survey, 13 were boys, 4 were girls, and 1 preferred not to say. Self-reported ethnicities were East Asian (n=11), South Asian (n=3), Caucasian (n=1), Mixed race (n=1), and Prefer Not to Say (n=1). Eight students

[1]https://www.polleverywhere.com/

were rising 12th graders, nine were rising 11th graders, and one was a rising 10th grader. 16 students self-reported prior computing and computer science classes. The most common AI-based products that students self-reported using were ChatGPT (n=18), Gemini (n=4), and Deepseek (n=4). Most students reported using LLM-based technologies like ChatGPT always (n=4) or often (n=10).

4.1 Model Lessons

We present two model lessons—one from the technical dimension (prompt engineering; L1-Prompt) and one from the socio-ethical dimension (misinformation; L2-MisInfo)—to illustrate how the ERR framework can be applied across different dimensions of AI literacy. Although we focus on these two lessons, the same structure was used throughout the course. In Section 5, we share how each component of the framework supported students' learning, application, and reflection. Section 6.1 offers guidance for educators on designing anchored activities for pre- and post-lesson activities.

L1-Prompt. The lesson began with two pre-lesson activities (step 1): a multiclass classification task on customer-service inquiries and drafting an argumentative essay (e.g., does AI have common sense?). Each activity was immediately followed by a PollEv activity debrief (step 2). During the activity debrief students shared how they completed the activity. The class-wide debrief for both lessons happened after both activities and activity debriefs were completed. During the pre-lesson knowledge check (step 3), students were asked to list any prompt engineering tips/tricks that they heard about or know. Depending on student responses, the instructor would signpost to upcoming lesson content. Then the instructor delivered the main lesson (step 4) and covered topics such as the structure of a prompt (e.g., user prompt, chat history, system prompt), defining the task-role-context in a prompt, and advanced prompt engineering techniques (e.g., retrieval-augmented-generation, in-context learning, chain-of-thought). After the lesson, students used PollEv to complete a 3 question knowledge check (e.g., List some of the best practices in prompt engineering.) (step 5). After each question, the instructor provided students with the possible answer options. The post-lesson activities (step 6) and debrief (step 7) followed the same structure as above. Students were provided the same multiclass classification task and an argumentative essay for a different context (e.g. is AI creative?). The class ended with a class-wide post-lesson activity debrief for both activities.

L2-MisInfo. The lesson began with two pre-lesson activities (step 1): question/answer with recent events (e.g., what team does basketball player Luka Dončić play for?) and finding 10 citations that you can use in an argumentative essay (e.g., should influencers be held to the same standard as journalists?). The pre-lesson activity and debrief (step 2) had the same structure as L1-Prompt. During the pre-lesson knowledge check (step 3), students were asked to explain why LLMs may generate incorrect responses. Then, during the instructor-led lesson content (step 4), students learned about different types of misinformation (e.g., knowledge cutoff, hallucinations, sycophancy) as well as their causes. For the post-lesson knowledge check (step 5), students were asked 4 questions (e.g., If LLMs are trained solely on factual data, would that eliminate misinformation? Why or why not?). For the post-lesson activity (step 6), the same activity tasks were given to students but in different contexts: question/answer (e.g., Which fiction book won the Pulitzer Prize for Fiction in 2024?) and finding 10 citations (e.g., Should people under 18 be allowed to have AI companions?). After each activity, students completed an individual activity debrief on PollEv (step 7). The class ended with a class-wide post-lesson activity debrief for both activities.

5 STUDENT LEARNING OUTCOMES AND FEEDBACK ON LESSON COMPONENTS

To evaluate the effectiveness of the lesson structure presented in Section 3.2, we analyze the student learning gains by comparing students' pre-course knowledge check with their post-lesson knowledge check answers (Section 5.1) and student feedback and utilization of specific lesson components (Section 5.2-5.4).

5.1 Student Learning Gains

L1-Prompt. After the lesson on prompt engineering, all students demonstrated an improved understanding of specific techniques that they could use, with many advancing from vague or uncertain responses to clearly defined techniques and explanations. Before the course, 11 of 18 students were unable to list any prompt engineering techniques. After L1-Prompt, all 11 students were able to define specific prompt engineering techniques such as *"system prompt, in-context learning, delimiters etc."* and able to explain why these prompt engineering techniques work. For the 7 students who were able to answer question, many used generic answers such as *"be specific"* or *"include as much detail as possible."* After the lesson, all 7 students demonstrated notable advances in their understanding by defining specific techniques that can be used.

L2-MisInfo. After the lesson on misinformation, all students were able to identify specific reasons why LLMs generated misinformation, with many being able to list at least 2 reasons. During the pre-course survey, 5 of 18 students were unable to list one reason. 13 of 18 students were able to list at least one reason for why LLMs might generate misinformation (e.g. missing data, inaccurate data). After the lesson, all 18 students were able to explain in detail why misinformation happens and identify different ways that misinformation can occur.

5.2 Anchored Activities (Step 1 and Step 6)

Through the post-course evaluation survey, all students either strongly (14 of 18) or slightly agreed (4 of 18) that the anchored activities supported their learning. S12 said: *"I felt like I could actually apply the concepts we learned through these activities."* We detail two ways that anchored activities support student learning: (1) fostering individual student sensemaking and (2) repeated exposure to the same anchored activity helped students apply the lesson contents to the same task.

Pre-Lesson Activities Support Individual Sensemaking (Step 1). Pre-lesson anchored activities can effectively support individual sensemaking by helping students independently uncover and understand key concepts. For instance, before L2-MisInfo, 82% (15 of 18) students were unaware of the knowledge cutoff (i.e., the date at which the training data for a specific model was last updated) as a reason for misinformation. During the pre-lesson activity debrief (Step 2), 11 of 18 students were able to identify the knowledge cutoff of the LLM by (1) discovering that the LLM produced misinformation when they used Google to fact-check the LLM-generated response, or (2) when the LLM output explicitly stated the model's knowledge cutoff date. S1 remarked that *"I asked the LLM first, but it didn't know the answer. So then I trusted the Internet's response,"* and S2 mentioned: *"I noticed that the outputs of the chatbot is limited to data until 2023... The questions the LLM fails to answer correctly is any question/answer that references information occurring after 2023."* This demonstrates that this anchoring activity helped students begin to conceptualize the knowledge cutoff.

Repeated Pre- and Post-Lesson Activities Support Applying Lessons (Step 1 and 6). Repeated exposure to the same pre- and post-lesson activity tasks allowed students to more explicitly apply what they learned and reflect on their metacognitive process to complete the task. In the post-lesson activity debriefs for the prompt engineering activity, we saw 17 of 18 students directly reference and apply techniques discussed in class: detailed instructions (n=8), system prompt (n=6), and in-context learning (n=5). Furthermore, in the post-lesson activity debrief, many students also explicitly mentioned what they did differently compared to the pre-lesson activity: *"I was more conscious about my wording and tried to incorporate in-context learning,"* (S1) *"The way I described the prompt to the AI was much more in detail and clear.,"* (S4) and *"I provided example responses this time"* (S6).

For the question/answer misinformation post-lesson activity, 9 of 17 students explicitly mentioned what they did differently compared to the first time they did this activity: *"This time, I stuck with the internet"* (S8), and *"Last time I used a LLM first and did not cross check my sources so they ended up wrong. This time I did a google search"* (S10).

This demonstrates that for an applied topic like prompt engineering or for a topic that students are less familiar with like the knowledge cutoff of LLMs, repeated exposure to the same pre- and post-lesson activity tasks allowed students to more explicitly apply what they learned and reflect on the metacognitive process they used to complete the task. Additionally, between the pre- and post-lesson activity reflections, students often directly reference the changes in how they approached the same task, revealing a metacognitive awareness of their learning.

Student Experiences with the Repeated Pre- and Post-Lesson Activities (Step 1 and 6). Some might think that students might find repeated exposure to the same activity task tedious. But we found that 7 of 17 students mentioned that the pre- and post-lesson activities were the most interesting part of the lesson for the prompt engineering lesson. S15 said *"The most interesting moment was when we tried the same classification task before and after learning how to engineer prompts,"* and another student responded *"The second part of the argumentative paragraph assignment, it was really interesting seeing the results of prompt engineering in an interesting way."* These comments demonstrate that some students appreciated the structure of repeated pre- and post-lesson activities because it allowed them to apply the prompt engineering techniques taught in class, but also supported them in comparing and contrasting the differences that prompt engineering can make.

5.3 Activity Debriefs (Step 2 and Step 7)

Activity debriefs helped facilitate individual and class-wide reflections. Individual debriefs were implemented via PollEv, followed by a class-wide discussion. 83% of students reported that these class-wide discussions supported their learning with students either strongly agree (12 of 18), slightly agree (3 of 18) or neutral (2 of 18). Activity debriefs supported students by providing an opportunity for peer learning and instructors by providing an opportunity to gauge students' prior knowledge.

Activity Debriefs Facilitate Peer Learning. During class-wide pre- and post-activity debriefs, students mentioned a variety of techniques or tools that they used to help them complete the activity. Students learn from each other and sometimes apply the tools and techniques they learned from their peers during the next anchored activity. For example, during the prompt engineering lesson, one student mentioned using Perplexity[2] to help generate references. Two students who originally did not use Perplexity used it during the post-lesson activity. S9 explicitly mentioned in the PollEv debrief *"I used Perplexity (since someone recommended it last time)."*. This finding aligns with prior work that explored the effectiveness of combining peer-discussion with instructor explanations. Especially as the technology behind LLMs continues to evolve, students who are active users and experimenters can help each other in exploring different ways these tools can be applied.

Activity Debriefs Help Educators Frame Lesson Content. Given the varying backgrounds and experiences that students have with AI, activity debriefs helped surface students' prior knowledge and experiences. For example, students who are more familiar with topics in prompt engineering might share advanced techniques like "in-context learning" during the pre-lesson activity debrief. This provides an opportunity to gauge classroom familiarity with the concept by asking the class to raise their hands if they are familiar with the topic. Additionally, it allows the instructor to signpost to upcoming content by saying things like "Later in the lesson, we will explore what in-context learning is and why it works!" For techniques not covered in the lesson, the educators can encourage students to explore these topics independently or provide resources for further reading.

5.4 Knowledge Checks (Step 3 and 5)

Overall, 94% of students either strongly (13 of 18) or slightly agreed (4 of 18) that knowledge checks supported their learning. One student was neutral. S8 said: *"I would say that the knowledge checks especially left a deep impression on me. It is kind of a nudge for us to have our knowledge better memorized, and I truly feel that this section greatly increased our efficiency of learning."* The knowledge checks were implemented on PollEv. S14 remarked *"I would definitely say the in-class activities and knowledge checks really reinforced the content due to its active recall."*

6 CONSIDERATIONS FOR IMPLEMENTATION

Our approach for implementing the ERR framework to technical and socio-ethical lesson in AI literacy helped support student learning and engagement. In this section, we provide recommendations

[2] https://www.perplexity.ai/

and considerations for educators who might want to implement the ERR framework for AI literacy lessons.

6.1 Design Decisions for Anchored Activities

One of the main lesson components of the ERR framework is the anchored activities. The goal of the anchored learning activities is to provide short activities that emulate real-world tasks where the parts of lesson content can be applied or demonstrated.

(1) **Define Desired AI Outputs.** For example, in L2-MisInfo, we explicitly designed anchored activities to elicit certain misinformation behaviors such as knowledge cut-off and hallucinations.
(2) **Consider How Students Might Already be Using AI.** For the knowledge cut-off, we chose the question/answer task, since many students are using LLMs information retrieval tasks and many search engines like Google have begun to integrate AI Overviews into its search feature [20].
(3) **Combine Desired AI Output with Common Student Tasks.** We designed current event questions that would not be in the training data for the model (e.g., GPT-4o has a knowledge cutoff of October 2023). But in order to differentiate the knowledge cutoff from hallucinations, we provide some events that might be in GPT-4o's training dataset (e.g., events that occurred before 2023) to provide nuances to the limitations of LLMs.
(4) **Tailor for Student Interests.** For this example, we tailored the anchored activities to the interests of the students (e.g., basketball, films, and music).
(5) **Design for Repeatability.** We expected that some students might make mistakes (e.g., using the LLM-outputted responses without fact-checking them) when completing the pre-lesson activity. By repeating the activity again at the end of the lesson, students have the chance to self-correct prior approaches and apply the lesson content, but not all activities benefit from repeated exposure. For L2-MisInfo, we had an in-class anchored activity where students learned about sycophancy and then used an LLM to generate a disinformation essay (e.g., false information which is intended to mislead). Once students got the LLM to generate a disinformation essay they accomplished the main learning goal: understanding how easily LLMs exhibit sycophantic behavior. Repeated exposure would not deepen this understanding.

6.2 Accommodating Different Class Durations

Given the number of interactive activities contained within the ERR framework of the AI literacy lessons that require time, the average duration of one lesson was around 2 hours. We recognize that not all educators have the time to integrate a 2-hour lesson into their existing class schedules, so we provide some recommended adaptations to the structure to fit different class durations.

For the lesson on misinformation, we covered (1) knowledge cutoff, (2) hallucinations, and (3) sycophantic responses all in the same lesson. As such, we included 2 different pre- and post-lesson activities and one in-class activity to provide students a hands-on opportunity to explore each of these topics. To accommodate shorter class periods, educators can instead teach one topic within misinformation at a time. Instead of applying the ERR framework to the entire domain of misinformation, the framework can be applied to a specific topic within misinformation, such as the knowledge cutoff. This approach would still maintain the practical structure of ERR while also accommodating a shorter lesson block. We estimate that this topic-based approach would be able to fit within a 60-minute class period.

6.3 Alternative Tools and Implementations

For our class, we used a a custom-web interface that supported additional features like system prompt, parameter controls (e.g., temperature, max_tokens, top_p), and different LLM models. For L1-Prompt, having the system prompt in the interface allowed many students to use this feature after the lesson to apply their learning. We would recommend that educators explore platforms like OpenAI's Platform Playground [28] or Together.AI's Web Playground [37] which provide online access to the same set of controls that we offer. But not all lessons require students to have access to these additional features. For L2-MisInfo, the main purpose of the questions is to elicit the knowledge cutoff and hallucinations from the language model which can be done though most chat-based LLM interfaces like OpenAI's ChatGPT [27], Anthropic's Claude [1], and Google's Gemini [15].

Using these platforms require setting up student accounts which may require additional administrative work and additional costs (e.g., costs of prompting the models). As such, educators can choose to instead implement the anchored activities as a class. Students can write down what they want the instructor to try and their thought process behind why and the instructor can select a few to test out. This approach merges the anchored activity with the debrief and can support a more collaborative approach to student learning. This approach may be especially beneficial for younger students with less technological familiarity or independence.

7 CONCLUSION

In this experience report, we design a lesson structure using the Evocation-Realization-Reflection framework and apply it to technical and socio-ethical AI literacy lessons. We find that anchored activities supported individual student sensemaking. Repeating the same pre- and post-lesson activity also supported students engagement and application of lesson content. We demonstrate how this lessons structure can be applied and provide recommendations for how educators can integrate this framework into their classrooms. We encourage educators to consider this framework when implementing lessons across the technical and socio-ethical dimensions of AI literacy.

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REFERENCES

[1] Anthropic. 2025. Claude. https://www.anthropic.com/index/claude. Large language model developed by Anthropic..
[2] Mordechai Ben-Ari. 1998. Constructivism in computer science education. *Acm sigcse bulletin* 30, 1 (1998), 257–261.
[3] Pengiran Hajah Siti Norainna binti Pengiran and Haji Besar. 2018. Situated learning theory: The key to effective classroom teaching? *HONAI* 1, 1 (2018).

[4] Virginia Braun and Victoria Clarke. 2019. Reflecting on reflexive thematic analysis. *Qualitative research in sport, exercise and health* 11, 4 (2019), 589–597.

[5] Cognition and Technology Group at Vanderbilt. 1990. Anchored instruction and its relationship to situated cognition. *Educational Researcher* 19, 6 (1990), 2–10.

[6] Digital Education Council. [n. d.]. What students want: Key results from DEC Global AI Student Survey 2024. https://www.digitaleducationcouncil.com/post/what-students-want-key-results-from-dec-global-ai-student-survey-2024

[7] Deepak Varuvel Dennison, Raycelle CC Garcia, Parth Sarin, Jacob Wolf, Christine Bywater, Benjamin Xie, and Victor R Lee. 2024. From consumers to critical users: Prompty, an AI literacy tool for high school students. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 38. 23300–23308.

[8] Brenda Dervin. 1998. Sense-making theory and practice: An overview of user interests in knowledge seeking and use. *Journal of knowledge management* 2, 2 (1998), 36–46.

[9] Ira Diethelm, Peter Hubwieser, and Robert Klaus. 2012. Students, teachers and phenomena: educational reconstruction for computer science education. In *Proceedings of the 12th Koli calling international conference on computing education research*. 164–173.

[10] Daniella DiPaola, Blakeley H Payne, and Cynthia Breazeal. 2020. Decoding design agendas: an ethical design activity for middle school students. In *Proceedings of the interaction design and children conference*. 1–10.

[11] Reinders Duit, Harald Gropengießer, Ulrich Kattmann, Michael Komorek, and Ilka Parchmann. 2012. The model of educational reconstruction–A framework for improving teaching and learning science. In *Science education research and practice in Europe*. Brill, 13–37.

[12] Glenn Ellis, Jake Lauer, Katie Silva, and Netty Nina. 2007. Assessing High School Girls' Preconceptions About Artificial Intelligence to Improve Learning. In *2007 annual conference & exposition*. 12–267.

[13] Sai Cheong Fok and EK Ong. 1996. A high school project on artificial intelligence in robotics. *Artificial intelligence in engineering* 10, 1 (1996), 61–70.

[14] D Ganesh, M Sunil Kumar, P Venkateswarlu Reddy, S Kavitha, and D Sudarsana Murthy. 2022. Implementation of AI Pop Bots and its allied Applications for Designing Efficient Curriculum in Early Childhood Education. *International Journal of Early Childhood Special Education* 14, 3 (2022).

[15] Google DeepMind. 2025. Gemini. https://deepmind.google/technologies/gemini. Large language model developed by Google DeepMind..

[16] Tom Hitron, Yoav Orlev, Iddo Wald, Ariel Shamir, Hadas Erel, and Oren Zuckerman. 2019. Can children understand machine learning concepts? The effect of uncovering black boxes. In *Proceedings of the 2019 CHI conference on human factors in computing systems*. 1–11.

[17] Tom Hitron, Iddo Wald, Hadas Erel, and Oren Zuckerman. 2018. Introducing children to machine learning concepts through hands-on experience. In *Proceedings of the 17th ACM conference on interaction design and children*. 563–568.

[18] Mahmoud Kaddoura. 2013. Think pair share: A teaching learning strategy to enhance students' critical thinking. *Educational research quarterly* 36, 4 (2013), 3–24.

[19] Ken Kahn, Rani Megasari, Erna Piantari, and Enjun Junaeti. 2018. AI programming by children using snap! Block programming in a developing country. In *Thirteenth European conference on technology enhanced learning*, Vol. 11082. Springer.

[20] Thashmee Karunaratne and Adenike Adesina. 2023. Is it the new Google: Impact of ChatGPT on students' information search habits. In *Proceedings of the 22nd European Conference on e-Learning ECEL*. 147–155.

[21] Qi Liu and Xiaorong Wang. 2009. The Anchored Instruction for programming courses: Cases, tasks and knowledge transfer. In *2009 4th International Conference on Computer Science & Education*. IEEE, 1549–1552.

[22] Duri Long and Brian Magerko. 2020. What is AI Literacy? Competencies and Design Considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–16. https://doi.org/10.1145/3313831.3376727

[23] Kurtis S Meredith and Jeannie L Steele. 2011. *Classrooms of wonder and wisdom: Reading, writing, and critical thinking for the 21st century*. Corwin Press.

[24] Luis Morales-Navarro, Yasmin B Kafai, Eric Yang, and Asep Suryana. 2025. What Can Youth Learn About Artificial Intelligence and Machine Learning in One Hour? Examining How Hour of Code Activities Address the Five Big Ideas of AI. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 39. 29195–29202.

[25] Luis Morales-Navarro, Daniel J Noh, and Yasmin Kafai. 2025. Building babyGPTs: Youth engaging in data practices and ethical considerations through the construction of generative language models. In *Proceedings of the 24th Interaction Design and Children*. 1021–1026.

[26] Davy Tsz Kit Ng, Jac Ka Lok Leung, Samuel Kai Wah Chu, and Maggie Shen Qiao. 2021. Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence* 2 (2021), 100041.

[27] OpenAI. 2025. ChatGPT. https://chat.openai.com. Large language model developed by OpenAI..

[28] OpenAI. 2025. OpenAI Playground. https://platform.openai.com/playground. Web interface for interacting with OpenAI's models..

[29] Timothy Paustian and Betty Slinger. 2024. Students are using large language models and AI detectors can often detect their use. In *Frontiers in Education*, Vol. 9. Frontiers Media SA, 1374889.

[30] Philip H Pollock, Kerstin Hamann, and Bruce M Wilson. 2011. Learning through discussions: Comparing the benefits of small-group and large-class settings. *Journal of Political Science Education* 7, 1 (2011), 48–64.

[31] Jean J Ryoo. 2019. Pedagogy that supports computer science for all. *ACM Transactions on Computing Education (TOCE)* 19, 4 (2019), 1–23.

[32] Jean Salac, Rotem Landesman, Stefania Druga, and Amy J Ko. 2023. Scaffolding Children's Sensemaking around Algorithmic Fairness. In *Proceedings of the 22nd Annual ACM Interaction Design and Children Conference*. 137–149.

[33] Jaemarie Solyst, Emily Amspoker, Ellia Yang, Motahhare Eslami, Jessica Hammer, and Amy Ogan. 2025. RAD: A Framework to Support Youth in Critiquing AI. In *Proceedings of the 56th ACM Technical Symposium on Computer Science Education V. 1*. 1071–1077.

[34] Jaemarie Solyst, Alexis Axon, Angela EB Stewart, Motahhare Eslami, and Amy Ogan. 2023. Investigating girls' perspectives and knowledge gaps on ethics and fairness in Artificial Intelligence in a Lightweight workshop. *arXiv preprint arXiv:2302.13947* (2023).

[35] Jaemarie Solyst, Cindy Peng, Wesley Hanwen Deng, Praneetha Pratapa, Amy Ogan, Jessica Hammer, Jason Hong, and Motahhare Eslami. 2025. Investigating Youth AI Auditing. In *Proceedings of the 2025 ACM Conference on Fairness, Accountability, and Transparency (FAccT '25)*. Association for Computing Machinery, New York, NY, USA, 2098–2111. https://doi.org/10.1145/3715275.3732142

[36] Elisabeth Sulmont, Elizabeth Patitsas, and Jeremy R Cooperstock. 2019. Can you teach me to machine learn?. In *Proceedings of the 50th ACM technical symposium on computer science education*. 948–954.

[37] Together AI. 2025. Together AI Web Playground. https://playground.together.ai. Web interface for testing and running LLMs provided by Together AI..

[38] David Touretzky, Christina Gardner-McCune, Fred Martin, and Deborah Seehorn. 2019. Envisioning AI for K-12: What should every child know about AI?. In *Proceedings of the AAAI conference on artificial intelligence*, Vol. 33. 9795–9799.

[39] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *Advances in neural information processing systems* 30 (2017).

[40] Alfred North Whitehead. 1953. *The aims of education and other essays*. New American Library of World Literature.

[41] Randi Williams. 2018. *PopBots: leveraging social robots to aid preschool children's artificial intelligence education*. Ph. D. Dissertation. Massachusetts Institute of Technology.

[42] Randi Williams. 2021. How to train your robot: project-based ai and ethics education for middle school classrooms. In *Proceedings of the 52nd ACM Technical Symposium on Computer Science Education*. 1382–1382.

[43] Anna Yaghobová, Michaela Mazná, Anna Drobná, Filip Děchtěrenko, and Cyril Brom. 2025. Principles of the Internet-Model Lessons for Lower Secondary School: Experience Report. In *Proceedings of the 56th ACM Technical Symposium on Computer Science Education V. 1*. 1274–1280.

[44] Helen Zhang, Irene Lee, Safinah Ali, Daniella DiPaola, Yihong Cheng, and Cynthia Breazeal. 2023. Integrating ethics and career futures with technical learning to promote AI literacy for middle school students: An exploratory study. *International Journal of Artificial Intelligence in Education* 33, 2 (2023), 290–324.

[45] Xiaofei Zhou, Jessica Van Brummelen, and Phoebe Lin. 2020. Designing AI learning experiences for K-12: Emerging works, future opportunities and a design framework. *arXiv preprint arXiv:2009.10228* (2020).

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