Investigating Collaborative Weaving Design as a Scaffold for AI Literacy

Carolyn Rosé, Carnegie Mellon University, cp3a@andrew.cmu.edu
Olivia Robinson, Carnegie Mellon University, orobinso@andrew.cmu.edu
Melisa Orta-Martinez, Carnegie Mellon University, mortamar@andrew.cmu.edu
Joey Huang, North Carolina State University, joeyhuang@ncsu.edu
Kylie Peppler, University of California at Irvine, kpeppler@uci.edu

Abstract: This poster presents version 1.0 of a curriculum unit designed to expose students to machine learning concepts related to representation and reasoning, an understudied area in AI literacy. Embedded within a textile art course, this three-week pilot explores whether hands-on weaving activities scaffold or distract from AI concept acquisition. Students design weavable potholders while engaging with an AI agent that demonstrates both capabilities and limitations of large language models.

Introduction

As generative AI technologies become increasingly embedded in daily life—from chatbots to recommender systems—students must develop the ability to critically evaluate these systems, understand their representational logic, and assess their societal impacts (Willige, 2024; Kafai et al., 2024; Kim et al., 2024). Despite increasing exposure to AI tools, even most undergraduates—particularly in non-STEM disciplines—lack this foundational understanding of how AI models represent and manipulate information, what their limitations are, and when human reasoning must take precedence (Veldhuis et al., 2025). Aligned with US AI4K12 (Touretzky et al., 2019) and other similar international efforts (UNESCO, 2022), curricular development and research in AI literacy has aimed to begin infusion of understanding and insight related to AI throughout K-16 education (Veldhuis et al., 2025). Many current AI literacy efforts focus on teaching how to use, configure, or even build AI-enabled services, tools, appliances, and toys (Kafai et al., 2024; Kim et al., 2024). However, another critical need is insight into what is reasonable to expect from current and future AI capabilities, and relatedly, what the continuing critical role of uniquely human capabilities will be (Kaspersen et al., 2021). This level of insight requires some understanding of what the reasons for the enduring limitations are and why they may not be obvious upon limited experience, or even the everyday experience with AI technologies that is now commonplace.

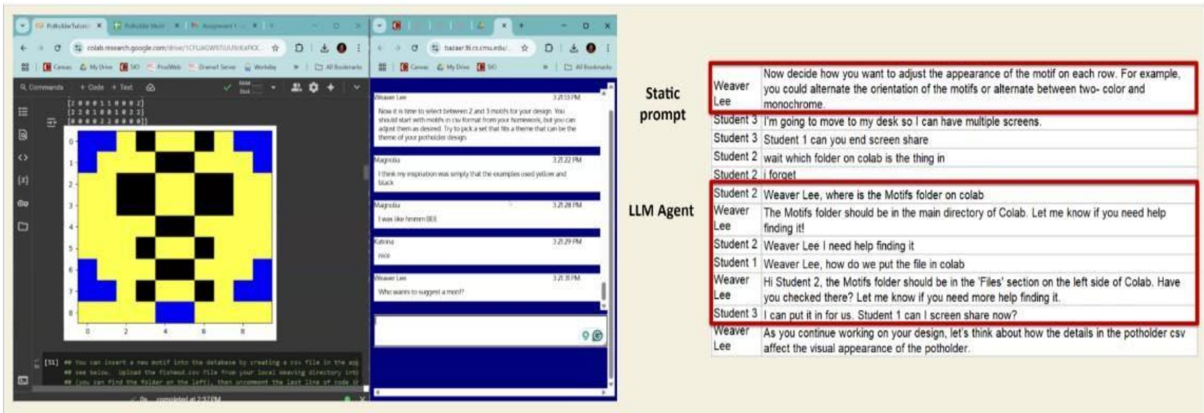
Curriculum materials

The key set of AI insights that this curriculum research effort focuses on is related to human-AI complementarity: the idea that humans and AI systems rely on fundamentally different strategies for problem solving. In particular, whereas humans excel at reasoning about abstractions and decomposing complex problems into smaller, generalizable steps, AI problem solvers struggle to form and use abstractions. In contrast to their human counterparts, AI systems manage to solve problems that require decomposition by retrieving similar cases from a potentially massive repository of past cases, which they may tailor in a limited way. Relatedly, when facing challenges during problem solving, humans are able to gradually adapt and improve a multi-step plan for a solution, while AI problem solvers are more likely to regenerate a solution from scratch, again by searching for a different prior case. At the surface, both strategies may frequently appear similar, and thus AI problem solvers are observed to provide impressive looking responses to a wide-range of queries. However, as researchers probe more deeply into the inner workings of AI problem solvers, it becomes clear that the apparent increase in capabilities of current AI models is mainly due to the massive increase in the size of both the models and the data repositories used to construct them.

To make these differences concrete, we use weaving on a shaft loom as a physical and conceptual analogy for machine learning representations. Weaving on a shaft loom provides a powerful physical embodiment of machine learning concepts, with the loom physically representing the multiplication of three matrices (threading, tie-up, and treadling). Students perform this multiplication by following weaving drafts, connecting embodied experience to abstract computation (i.e., matrix factorization). Designing weaving patterns further mirrors how machine learning breaks down complex patterns into underlying representations. Students must find the right level of abstraction (i.e., detailed enough to preserve desired structure, but general enough to be woven), mirroring the machine learning tension between overfitting and underfitting, To make designs weavable, students must simplify them to emphasize regular, hierarchical structures in order to use the computational power of the shaft structure judiciously. This parallels how ML models compress complex data into lower-dimensional embeddings, often losing information in the process (i.e., compression and approximation). Finally, just as looms place physical limitations on what patterns they can produce, neural networks have representational constraints that limit their capabilities (representational constraints).When designing, students work in a collaborative digital environment featuring a shared Jupyter notebook for interactive programming, integrated chat tool for team communication, and an AI facilitation agent (named "Weaver Lee") that provides both structured guidance and demonstrates LLM limitations in real-time (Figure 1). Weaver Lee functions as both a collaborative design assistant and a critical reflection scaffold. It prompts students to iterate on designs, surfaces contradictions in abstraction, and occasionally fails in subtle ways, prompting metacognitive discussions about the limits of LLMs. It is designed around principles of productive failure and epistemic agency, helping students develop a calibrated understanding of what AI can and cannot do. Just as introduced earlier, the shaft loom's representational limits provide a tangible counterpart to the compression and compositional challenges inherent in neural network representations .

Despite their limitations, LLM agents are able to serve as facilitators of collaborative learning sessions. By focusing on tasks well-matched to LLM capabilities, such as using reflection prompts to support learning in collaborative software development (Naik et al., 2024, 2025), we can more effectively leverage GenAI in practice. We take a similar approach to that taken in Naik's (2024; 2025) past work with AI agent support for collaborative engagement with the activity. The current pilot did not separately analyze the specific impact of the AI agent on learning outcomes.

Figure 1
Collaborative Design Environment (on left) and Example Interaction (on right).



Pilot

A small pilot of the three-week unit was conducted in an undergraduate interdisciplinary textile art course at a mid-Atlantic university. Four teams of students (N= 12) engaged in a potholder design task that required them to work across three representational levels: raw matrix data, loom mechanics, and high-level pattern logic. Students completed a pre-assessment after engaging with the assigned reading and interactive lecture introducing the core concepts. Because the pre-assessment followed this initial instruction, it does not serve as a baseline measure of prior knowledge, which was intentional because the goal was to measure learning specifically during the collaborative design portion of the unit. This, the pre–post comparison reflects any shifts in understanding that occurred during the design and reflection phases. The three-week period of time during which they engaged in the design activity began with individual design work, with a single collaborative session in the middle, and final individual finalization of the design. Overall, the results from the pilot study suggest that during the design and reflection, students moved away from a task focus and towards engagement with AI concepts. However, their written answers demonstrated that they still did not reach mastery. While the quantitative comparison between pretest and posttest focusing on multiple-choice questions demonstrated substantial learning gains, the fact that students continued to struggle with abstract symbolic constraints suggests a need for more structured support in transitioning from concrete activities to analogous abstract reasoning, which will be addressed in subsequent work.

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