Collaborative Intelligence: Towards Practical, Critical and Cooperative Teaching & Learning with AI

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Abstract

In response to the significant disruption posed by emergent AI technology, we propose a four part framework for teaching and learning practice and development. Rather than focus on the specific technologies of the moment, this framework provides actionable suggestions for individuals with varying views of AI and its positive and negative consequences. Exploring algorithms as an instructor, interrogating course learning outcomes, and applying algorithmic literacy in learning environments are useful starting points when considering disciplinary education in the future. However, it is only when done in concert and cooperation with students that these teaching actions will become responsive to future algorithmically-based technologies.

Keywords: *artificial intelligence, higher education, algorithmic literacy, pedagogical partnership, co-creation, learning outcomes, critical pedagogy, student-instructor partnership, transformative action, assessment design*

We write in response to rapid advancements of Generative AI and the significant impact it has on teaching and learning practice in higher education.[1] Justin Reich and Jesse Dukes characterize the unique circumstances of AI as a technology that arrived quickly, in comparison to gradually adopted tools (Reich & Dukes, 2024). Previous advancements like the internet or in-class response systems offered time, with multiple opportunities to react and guide decisions about design and implementation. This slower pace allowed educators to develop their philosophies, with far less disruption to teaching practices honed over many years (Klopfer et al., 2024). In contrast, widespread accessibility of frontier-level large language models (LLMs) allows every college student to query a highly sophisticated algorithm that can infer their textual input, interact dynamically with the user, and produce text that closely mimics the expected responses on standardized assessments. This algorithm also provides non-standardized output, changes regularly, and is much more applicable in certain circumstances than in others.

The rapidity in AI's arrival complicates existing assessment structures and invites a variety of opinions and responses to its value and utility. While most of the early scholarship on AI and learning is either highly critical or strongly optimistic (Bender et al., 2021; Mollick & Mollick,

1. The authors acknowledge that no Generative AI technology was used to author language in this chapter. The ideas presented are solely those of the authors and the declared authors of literature cited herein.

2024), our work here offers practical guidance for teachers and administrators, inclusive of multiple philosophical views of AI. Literature exploring the impact of AI on teaching and learning largely ignores student perspectives. One analysis highlights that the student voice received as much attention as ChatGPT's in scholarship (Sullivan et al., 2023). Student co-authorship, as modeled in this article, remains rare. Educators will spend years grappling with the integration of AI into their course structure, but that enterprise can be significantly improved by directly incorporating students into the learning process.

Current LLMs achieve high levels of proficiency on a variety of assessments in higher education. By 2023, large language models already demonstrate top quartile or decile performance on professional exams like the United States Medical Licensure Exam (Brin et al., 2023; Nori et al., 2023), the North American Pharmacist Licensure Examination (Angel et al., 2023), the Pediatric Board Preparatory Exam (Le & Davis, 2024), the Graduate Record Exam (Abu-Haifa et al., 2023), and the Graduate Management Admission Test (Ashrafimoghari et al., 2024). Frontier models have similarly performed well on standardized disciplinary assessments. Preliminary research shows satisfactory completion of tests in biochemistry (Ghosh and Bir, 2023), engineering (Pursnani et al., 2023; Gong et al., 2023), neurosurgery (Schubert et al, 2024), physics (West, 2023), and economics (Geerling et al., 2023).

However, as predictive machines, exam-caliber LLM outputs are simply "statistically likely" word combinations with significant possibility for errors or factually incorrect statements. While this may change in the future, LLMs often lack satisfactory outputs in specific use cases, like accounting (Abeysekera, 2024), nutrition plans (Niszczota & Rybicka, 2023), visual-spatial analysis (Zhang & Wang, 2024), clinical contexts (Qazi et al., 2024), and mathematical and physics equations (Zhang et al., 2024). The machines also can erroneously infer queries where social or cultural knowledge would substantially change the desired output. For example, while LLMs are excellent at introductory computer programming examples, they demonstrate regular failures at realizing a user's intent (Liu et al., 2024). Similarly, LLMs can analyze swaths of scholarly literature, but they do not match humans at evaluating the rigor of existing studies (Woelfle et al., 2024) or synthesizing comprehensive literature reviews (Arora et al., 2023; Wang et al., 2024).

The probabilistic structure of AI creates two unique challenges, previously absent from most technologies that influence cognitive work. First, their output is necessarily unpredictable. Responses to user queries vary from person to person and can change regularly. While some outputs may be common, AI provides individualized experiences. Second, while AI can infer a user's instructions in a novel manner, using AI introduces uncertainty into the production and evaluation of language, even as it presents its output as certain. Thus, AI forces us into the intersection of disciplinary knowledge and uncertainty. When it comes to teaching, we tend to live in the realm of the certain, which is predictable and forms the basis for most approaches to teaching and course design.

In sum, we have a widespread technology that is suddenly available, using existing devices via an accessible chat interface. Wholesale evaluation is difficult and full of potential errors and biases because the output is not consistent, is valued differently by different users, and the tools are updated regularly without transparency or user guidelines (Ma et al., 2024). Yet, they successfully complete many college homework assignments and common high stakes assessments. How can educators and students respond to this?

Several scholars have released preliminary frameworks or guides to help instructors decide how they might integrate AI into coursework. Leon Furze and colleagues have provided an AI Assessment scale that outlines different levels of engagement with AI in assignments (Furze et al., 2024). Ethan and Lilach Mollick provide examples of practical uses of AI in personalized learning efforts with instructor guidance (Mollick & Mollick, 2024). Maha Bali offers five steps to interact critically with AI, prioritizing student awareness of biases and ethical costs to their use alongside practical lessons on prompting and direct engagement (Bali, 2024). These approaches are particularly helpful for the immediate concerns of instruction in response to an emergent, widespread and disruptive technology. Yet, they remain focused on short-term practices and assume a general embrace of AI.

Our efforts here prioritize individual professional development. We accept that AI already significantly disrupts teaching and learning behaviors in higher education, and strongly suggest that educators transition from traditional assessment methods to more holistic and interpersonal learning activities and assignments.[2] Our contribution outlines four steps for educators to craft learning environments while fostering critical student engagement with AI. We present these steps as a progression with each one requiring more time, energy, and thought. All of these steps are rooted in robust scholarship, they do not require active engagement with AI tools, and they are not tied to specific AI tools and are thus less likely to be obviated by new technological advances. They comprise a path for thinking through how you want your students to learn and how you can encourage them to engage with the mentally taxing effort that learning requires. They are also accompanied by examples of implementation and student-instructor experience. We suggest you should:

1. Explore algorithms to develop your critical lens
2. Develop and prioritize course learning outcomes with interpersonal and affective goals
3. Apply algorithmic literacy in learning environments
4. Engage in the co-creation of learning with students

Exploring Algorithms to Develop Your Critical Lens

Despite the ubiquity of algorithm-driven technologies (Just & Latzer, 2017), most of us have little clarity on how these algorithms function, the human intentions and socioeconomic structures behind them, and how they contribute to the broader societal impacts we see in the news, in social media, and in our day-to-day interactions (Cheney-Lippold, 2011). In an AI-saturated information landscape with blurred lines of authority, investigating *how* and *why* information originates before analyzing the information will become increasingly valuable to learners.

Teaching information literacy traditionally followed a rote process of collecting a prescribed number of scholarly publications to support one's views in an essay or annotated bibliography, rather than an exploratory learning process (Holliday & Rogers; Fister, 2022). This learning experience occurs in the controlled, curated environment of library databases, course reading lists, and peer-reviewed journals. Generative AI tools and algorithm-driven social media platforms are disruptive technologies necessitating the re-definition of modern information literacy (Wineburg et al., 2020; Eguchi et al., 2021; Head et al., 2019; Swart, 2023). Since the advent of ChatGPT, attempts to define algorithmic literacy have exploded in the literature across disciplines, particularly in the bodies of information literacy, communication, and education literature (Archambault,

2. The authors represent three professional perspectives: A professor of library sciences, scholars from a teaching & learning center and a student researcher. We also blend disciplinary backgrounds of English, education, history and psychology.

2023; Augustinus, 2022; Oeldorf-Hirsch & Neubaum, 2023). From algorithmic awareness to algorithmic skills, the concept of algorithmic literacy continues to evolve, but because of AI's multifaceted nature and varied integration across disciplines, there is a persistent lack of agreement upon any centralized definition or standards for algorithmic literacy or AI literacy (Oeldorf-Hirsch & Neubaum, 2023). Our framework builds on these varied definitions, progressing from initial responses to AI to a proactive applied framework developing a co-created understanding of AI, how it shapes our behavior, and its broader societal impacts. We contextualize algorithmic literacy within a model for pedagogical development, emphasizing critical engagement with AI.

Understanding how AI works and applying a critical lens to algorithmic output and its role in your course allows you to guide your students through their engagement. Because many instructors outside of computer science fields are generally unsure about how to approach AI in teaching and learning (Ghimire et al., 2024; Damiano et al., 2024), we have provided several different perspectives below that may serve as a template for your thoughts.

Perhaps you connect with scholars who oppose AI and are highly skeptical of the myriad claims of transformative possibilities for technology like LLMs (Bender et al., 2021). You critique efforts to ascribe AI output as "thinking", realizing that they are simply using math to generate a series of words (Royer, 2024). You characterize LLMs not as "magic machines" but predictive responses to human textual input, and resonate with warnings of the potential harms to learners who may outsource the deep learning activity of organizing their thoughts through writing. You are concerned that students will substitute machine-generated summaries for their own comprehension. You recognize the bias reinforced through algorithmic output, and are critical of the largely unregulated economic, social and environmental costs of AI (Gray & Suri, 2019; Muldoon et al., 2023; Kalluri et al., 2023; Weinberg, 2024).

Perhaps you are uncertain about AI and align with individuals interested in learning more about it. You have heard claims from your colleagues about the effectiveness of LLMs to facilitate cognitive labor of teaching. You are concerned about student work, noticing an increase of grammatically accurate but sometimes bland, irrelevant writing in response to homework or essay prompts. You wonder how AI could help certain portions of the learning experience but worry about adverse effects for learners who come to rely on it (Warschauer et al., 2023). Your administration likely provided limited or unclear policies on AI use for students and teachers (Luo (Jess), 2024). In short, you would like to learn more, but are unsure where to start and how you might gauge the potential impact of AI in your courses.

Perhaps you are among the early adopters of AI. You have read with interest the academic conversations about using ChatGPT or a custom LLM to augment your work (Guralnick et al., 2024). You have spent some time using and exploring these tools. Maybe you have attended development workshops and seminars or explored literature about the relative effectiveness of LLMs on standard assessments. You have engaged students in conversations about their use of AI tools and are exploring how to modify your course and teaching practice in response.

Perhaps you are a strong advocate of AI and LLMs. You see fantastic potential for their use and multiple possible improvements for your own workload (Yin et al., 2024; Lai et al., 2024). You have been using these tools for many months, including paid frontier models, and have integrated them into your inquiry, teaching and administrative work (Mollick, 2023). Maybe you have incorporated these tools directly into assignments. Perhaps your institution has an agreement with an AI provider, and you have explored this tool with your students (Swack, 2024). You see the future of AI as a fundamental change in the way students will learn (Walter, 2024).

Adherents of these different perspectives will choose different pedagogical approaches in the classroom. As you engage with teaching in response to algorithms, you might elect to share cautions for over reliance on information coming from AI resources. You might want to convey the lack of nuance and the generic organization of information that chatbots generate. You might favor intentional critical discussions of disciplinary decision-making, and use AI as a ready-made example for students to test their learned skills and knowledge as evaluators of concepts and information. All of these efforts begin with the construction of learning outcomes, and the introduction of AI spurs us to revisit our course outcomes and consider how this technology may complicate them.

Interrogate Learning Outcomes

The last two decades have witnessed significant institutional investment in developing and measuring learning outcomes that increase transparency and intentionality in student learning (Reinventing Undergraduate Education, 1998). However, these outcomes remain disproportionately focused on cognitive skills (Riley, 2016). In foundational courses memorization and explanation of phenomena are predominant in both course delivery and assessment (Welch et al., 2005; Momsen et al., 2010). LLM output mimics explanation and recall particularly effectively. While more cognitively demanding outcomes initially offered a way to subvert AI's output for assessment (Bala & Colvin, 2023) more recent models mimic synthesis and evaluation tasks as well (Schubert et al., 2023). While AI does not obviate learning outcomes and goals, the availability of AI mimicking human outputs arguably places greater importance on skills and deep understanding. We are stimulated to prioritize and possibly reframe our learning outcomes.

Prioritizing learning outcomes will enhance any learning environment and allows us to change courses dynamically in response to emerging needs (Levesque-Bristol, 2021). Many guides on creating outcomes focus on external accreditation requirements and institutional priorities. Often, these approaches fail to prioritize and structure outcomes holistically. The challenge for us as instructors is to assign priority to those outcomes pre-emptively so we can more easily modify our instruction in response to technologic or extreme scheduling events (Oliveira et al., 2021). Historically, outcomes are constructed around a cognitive verb, often from an "approved" list by dimension (Stanny, 2016). Examining a verb list like this and comparing against your existing outcomes can spur an evaluation of what you really want your students to know or be able to do after having completed your course.

One strategy for prioritizing outcomes involves a hypothetical scenario where you are informed of a transition from 15-week semesters to 10-week quarters, and you must remove one or more outcomes, and rank the remaining outcomes according to importance for the course's integrity. This may involve combining two or more outcomes, and possibly focusing on higher-order cognitive skills and sometimes affective and interpersonal skills. The types of lower-order cognitive tasks present in many learning outcomes, especially in introductory courses, are most susceptible to AI's mimicry. Though higher-order cognitive tasks like analysis and synthesis are not inured against AI replication (Ghosh et al., 2023; Bharatha et al., 2024; Street et al., 2024), they often involve more process steps than simple explanations, allowing for greater exploration and deeper learning (Antonio & Prudente, 2024).

While interrogation and exploration of cognitive outcomes can increase flexibility and transparency, they offer limited opportunities to measure holistic intellectual growth. Disciplinary education also involves values, beliefs, perspectives and discussion. It accentuates students' ability to communicate, persuade and collaborate to achieve things beyond individual capabilities. Groups, dialogue and debate matter in a college education. Yet, we are often remiss in explicitly including this growth in course learning outcomes. The relegation of these elements to an implied curriculum misses opportunities, as evidence advances the notion that interpersonal support can foster a stronger sense of well-being and satisfaction of basic psychological needs (Slemp et al., 2024).

AI does not offer meaningful ways to simulate development of affective skills and interpersonal aptitude (Dong et al., 2024). At the time of publication, most frontier models are designed to indicate reluctance to generate value or belief statements (Chun & Elkins, 2024). AI cannot currently read subtle facial expressions or synthesize long, contextual knowledge of an individual person's preferences or philosophical world view. They cannot internalize the emotions of a user's tone or the gravity that they might assign to a particular argument. A student's simultaneous synthesis of gradual and immediate social interactions should be as important as their ability to explain a chemical reaction or solve an equation, so we can layer them into our process more explicitly and structure opportunities for students to reflect on their interpersonal progress in a learning environment. Prioritization of course outcomes facilitates the, layering of specific affective or interpersonal outcomes.

Moving deeper, recognizing the rapidly changing nature of AI tools, the variety of experiences students bring to these tools, and the diverging applications students will embark on in the future, we suggest co-creating one or more learning outcomes with students. We see great promise in incorporating AI-related learning outcomes developed in partnership with students, such as a collective course outcome (Bovill, 2020). Co-created outcomes often center on collective work, and students can determine the parameters, whether in small groups, as a whole class, or divided up into teams. Co-created outcomes at the classroom level often use a democratic process. This can involve a single majority vote or can model different approaches to democratic decision-making (e.g., ranked choice voting).

Co-created outcomes can also be individualized, where students have slightly different versions of an outcome. The most frequent model for these outcomes emerges from classroom participation (Gillis 2019) where students set and reflect on individual goals for what classroom engagement and participation means to them (recognizing differences in experience, comfort, and personality). We can take a similar approach to a goal focused on engagement with AI tools, where students set goals for incorporating AI tools into their working and learning process within the particular discipline and reflect on progress during the semester.

Many institutions require advance documentation of course outcomes, which can interfere with co-creation. In this situation, we can use broad framing of an outcome that empowers students to define individual approaches to success. For example, an outcome can be: "Interrogate your relationship with AI tools in the process of engaging with [discipline] and develop a framework for future development as new tools emerge". Or, "create and implement a project that connects AI tools with your individual goals in [discipline/field]". These open outcomes benefit from multiple opportunities for metacognitive reflection and open-ended assignment structures such as Unessays (Gillis, 2019) and non-disposable assignments (Seraphin et al., 2019).

Analyzing, prioritizing, and modifying your learning outcomes fosters intentionality in your teaching decisions. Integrating affective and interpersonal outcomes into a course redirects the focus to our shared humanity and collaborative knowledge creation. Co-creation of learning outcomes with students prioritizes their role and responsibility in the collective learning process. These progressive steps will make your teaching more responsive to AI's impact on assessment and activities, while providing a structure if you wish to integrate algorithmic literacy into your course.

Apply Algorithmic Literacy in Learning Environments

Our algorithmic literacy approach comprises four guiding principles for instructors and students to co-design learning experiences that account for the impact of AI: 1) process orientation, 2) inquiry, 3) reflection, and 4) transformative action. Each pedagogical approach is entwined with the others, but we present them here as a progression of practice. First, process-oriented learning develops metacognitive and cognitive skills around algorithmic awareness, which forms the foundation for more complex learning practices of inquiry and reflection. Finally, these practices together can result in transformative classroom action with and about AI.

Algorithmic literacy pedagogy extends critical information literacy's practice of examining social structures and power dynamics behind information (Downey, 2016; Elmborg, 2006; Drabinski & Tewell, 2019). Traditionally, socially-constructed signifiers of authority guide evaluations of information's reliability, but realistically, it is challenging for non-experts to contextualize expertise. Students are often compelled by surface-level appearances of neutral authority, now even more easily generated with AI tools (Wineburg, 2020). Instead, algorithmic literacy pedagogy takes a broader, more systemic approach to the ways we use information to learn. It directs students' to question the assumed neutrality of AI tools,evaluate the algorithmic *information systems* that now determine which information we see, and examine how those systems are intertwined with social structures and human outcomes (Noble, 2018).

If we want a society that approaches AI and algorithms critically, it is necessary to challenge the traditional instructor-student power dynamic, where learning equates to passive reception and reproduction of information. Otherwise, we risk students affording authority to AI as a "neutral" distributor of knowledge. Conversely, pedagogical partnership brings students into classroom decision-making, creating a culture and expectation of mindful engagement and participation in knowledge creation, and forms ways of thinking that naturally challenge the very easy tendency to allow AI to "think for us."

The disruption that AI has realized is an ideal opportunity to engage students in such a partnership. Most, if not all, of us have limited expertise responding to this new technology. While we have disciplinary expertise and experience with critical thinking as a result of our training, instructors and students are starting on relatively equal footing. We can collaboratively learn how to retain our decision-making power in the presence of technology designed to automate decision-making processes.

Practice One: Process Orientation

Critical engagement with AI prioritizes a process orientation to learning. Through pedagogical partnership, students engage more fully in understanding and directing the processes of learning (Bovill, Cook-Sather & Felten, 2011). A focus on process spurs self-regulatory cognitive strategies that result in the transfer of control over learning from instructor to student, supporting students' awareness to use AI to enhance learning rather than replace it (Baron Levi, 2020). Basic knowledge of the technical processes *and* social power dynamics behind algorithmic platforms provides clarity on how and why we receive particular information. Algorithmic literacy encourages consideration of the personal side of these processes - how our own cognitive, affective, and behavioral processes are impacted by algorithmically-mediated information.

We suggest four process-oriented strategies to develop algorithmic awareness (Augustinus, 2022; Long & Magerko, 2020). Implemented in pedagogical partnership, instructors and students construct algorithmic awareness collaboratively. Partnership strikes a balance between valuing disciplinary proficiency and inter-disciplinary innovation when developing algorithmic literacy - instructors bring a seasoned disciplinary thinking perspective and students contribute creative possibilities for exploring and applying new knowledge with AI tools (Kreber, 2010). Instructors can model and practice a combination of general or discipline-specific algorithmic awareness strategies with students to develop a shared ethic around effective processes for learning with AI:

1. Problematization of algorithms in daily information interactions
2. Exploration of algorithmic platform functionality
3. Evaluation of the strengths and limitations of algorithm and human capabilities
4. Integration in decision-making of ethical and social impacts of use (or not) and regulation of algorithms

These habits of mind integrate fundamental skills and knowledge about the nature and functionality of algorithmic technologies. They can be approached broadly, in the context of personal information use, or in the context of interaction with information in a particular discipline or field. A process orientation positions students to direct their own learning, apply it across contexts, *and* see the impact of their work beyond themselves.

When the desired outcome of learning is knowing *how to learn*, using AI tools to do the work for you can be less appealing. Consider having students collectively explore an AI tool's capabilities and share findings or challenges encountered. At each step in the process, ask students to describe what they are doing and seeing, and why they think it might be happening. A class could explore differing outcomes of completing the same task if each student uses the same prompt with an AI tool or, alternatively, if each student writes a unique prompt to use with the same AI tool.

This critical and collective process approach counters the lure of AI as a tool for accelerated information gathering and evaluation. Consider OpenAI's "Students' Guide for Writing with ChatGPT", which encourages users to "delegate citation gruntwork" or "jumpstart your research" through the chatbot ("A Student's Guide, 2024). Much of the guide assumes individual prompting with a machine as superior to interpersonal discussions in a collaborative learning environment or time spent engaging in reflective thought. It encourages idea development through intellectual sparring with the chatbot, subordinating dialogues with peers or engagement with scholarly sources, and posits cognitive labor as something to be overcome (Nelson, 2024). When we view the outcomes of courses as the transaction of student enrollment for a set of products, the students are the barriers to successful completion and we should not be surprised when some select expedited avenues for task completion. Instead of this oppositional framework, a process orientation supports collaborative valuing of the exploration involved in learning, especially the central lessons that emerge from errors and that reveal our opportunities to grow and develop.

Practice Two: Inquiry

Algorithmic literacy pedagogy cultivates a toolkit of inquiry, by which we seek informational context—not just content—as a necessary component for decision-making (Caulfield, 2017). Inquiry-based learning highlights the decision-making process in specific disciplines. In pedagogical partnership, instructors can share the power of asking and investigating questions that are personally meaningful. As students practice using AI tools to ask questions and increasingly share decision-making power, they bring more of themselves to academic work. Not only can they practice disciplinary decision-making, but the learning process also can be increasingly self-motivated (Bull et al., 2021; Cook-Sather et al., 2014; Head et al., 2019). When starting a course or a new unit, consider having students search independently for information about how AI could be used for learning generally, for a particular topic or task, or for professional work in a particular field, and then share their findings.

Practice Three: Reflection

Reflective practice is particularly essential in algorithm-mediated information seeking, where the platforms are designed to simplify the information gathering process by removing as many steps as possible. This efficiency and convenience offers a tradeoff, facilitating discovery while simultaneously limiting motivation for critical analysis (Wineburg et al., 2020). Driven by economic motivations to maximize user engagement, algorithmic platforms also tend to prioritize information that will generate an immediate, emotion-driven reaction. (Bucher, 2018; Noble, 2018).

Pedagogical partnership engenders reflective practice in both partners as they regularly receive feedback about their actions and assumptions from a partner who sees learning from a different perspective (Cook-Sather & Abbot, 2016). Reflection benefits learning, professional work, and personal growth. It deepens and documents learning, provides clarity on the purpose for our actions, and informs next steps for decision-making (Ash & Clayton, 2009). The reflective nature of partnership creates necessary moments to critically examine motivations behind use of AI and the origins of information it provides. Integrating reflective exercises into coursework can develop a practice of pausing to examine how our preconceptions and emotions impact our perception of a source's accuracy or trustworthiness (Oeldorf-Hirsch & Neubaum, 2023). Self-evaluation can be an intimidating and unfamiliar practice, so structured guidance provides easier entry. Regular student check-ins with an instructor provide opportunities to identify areas of both strength and struggle, as well as build relationships. The benefits of these reflective meetings demonstrate that learning and information are socially networked, and by extension, that AI tools cannot replace the unique affordances of human-to-human interaction, even if they can supplement them.

Here we introduce our student co-author’s perspective on reflection and student AI use:

> I [author Anaelle] observe diverse ways in which my peers approach LLMs and incorporate them into their studies. Generally speaking, many express to me their awareness of AI’s notable weaknesses, including its inability to compute accurate outputs for mathematical questions and its peculiar vocabulary. Yet, the extent to which students critically analyze the information generated by these tools is difficult to gauge. Students commonly use AI to save time by automating work deemed inessential to our intellectual development, including writing emails, cover letters, and discussion posts in professional and

educational settings. Unclear expectations for work, pressure to complete assignments accurately and promptly, or lack of confidence in one's knowledge or abilities, may lead to diminished intrinsic motivation, anxiety, procrastination, and, in turn, unethical uses of AI to generate classwork. Student involvement in determining learning goals and assessment measures may reduce stress and anxiety associated with externally imposed expectations. In this sense, student-instructor partnerships foster an openness to engage in the exploration of information, ultimately minimizing the inclination for my peers to utilize AI as a mental shortcut.

Herein lies the challenge for instructors to portray academic material as applicable to students' real-life experiences. A student's decision to use these tools is highly context-dependent and varies across disciplines, duties, and goals. In the eyes of my peers, AI is particularly skilled at generating ideas for unfamiliar subject matters. A conscious effort to think carefully through problems and tasks is a time-consuming act students may not complete if a technology can quickly produce satisfactory results. We are rarely granted the time as students to engage with the unknown, instead we are guided towards certainty. As a means to address undetectable plagiarism associated with AI's ability to mimic student work, instructors who police their classrooms will not better identify original work nor will they understand how students are currently doing it. Instead, I strongly suggest instructors assess how students demonstrate conscious effort to think carefully through problems rather than producing satisfactory ideas or results.

I recognize a novel form of creativity and problem-solving associated with student interaction with AI. Students develop prompts for these tools and learn to navigate them independent of their instructors. However students choose to incorporate AI in their work, we experiment with these tools' capabilities and pitfalls. Students can cultivate problem-solving and reflection by intentionally engaging with AI in collaborative spaces.

Engage in the Co-Creation of Learning with Students

Our approach suggests that it is most powerful to develop AI literacy in coordination with students. Drawing on the tradition of critical pedagogy (Freire, 2005; hooks, 1994) in coordination with viewing students as partners (Cook-Sather, Bovill, & Felten, 2014), we advocate an opportunity to interrupt the power imbalance traditionally embedded within the higher education systems (Mercer-Mapstone & Abbott, 2020) and treat students as co-creators of new knowledge and practices. Doing so presents numerous challenges to the traditional frames and attitudes around planning and teaching a class, but we believe it also exemplifies the potential for AI tools to expand access to knowledge, resources, and education. In this section, we describe specific policy structures that can be incorporated into classes leading toward a co-creative structure, but first, we highlight some of the more common AI class policies and approaches.

No Policy

Unfortunately, the most common AI-related class policy remains no policy. We believe this often stems from fear of the unknown, and sometimes a fear or mistrust of students. Instructors do not avoid having AI-related policies because they are unaware of AI or even how it can fit into supporting student learning in their discipline. In many cases, public overstatement about the capabilities and widespread use of AI tools (e.g., "ChatGPT is a Plagiarism Machine" by Keegin,

2023) can exacerbate a fear/belief that maintaining the class structure requires banning AI tools. Many instructors rely on existing language about academic integrity and the fact that one's work might not be their own. This approach is likely to find less success and greater uncertainty as AI tools become directly integrated into many common working tools and structures. For example, few instructors would ban spelling and grammar check services, yet tools designed for this purpose promote their enhanced integration of AI (Quellman, 2024). Some tools already occupy this gray area, like PowerPoint designer, which automates color schemes and adds icons to slides. Yet, we imagine few classes or situations where students would assume a blanket AI ban would prohibit PowerPoint designer.

Faux-Creation: How AI Sometimes Reveals the Limits of Instructor Power-Sharing

As in the reflection above, when [Author Anaelle] experienced a class that otherwise focused on creating a collaborative and co-created learning environment, the absence of AI policies on major projects and assignments became a glaring omission to students. One of the most interesting trends we have observed is how the introduction of AI tools and the uncertainty they bring can sometimes test the limits of instructors' stated dedication to co-creation, leading to the structure we call faux-creation. In the AI faux-created class, instructors enact many components of co-creation. They may give students opportunities to share input on course content, develop personalized learning outcomes or objectives, and design different ways for them to express their learning through flexible assignment structures. They also allow students input into class policies, like attendance and late-work, or group and peer engagement. However, they limit student co-creation around AI. We perceive this limitation in co-creation as emerging from the same fears of those who avoid an AI policy, and we find that it unfortunately has the effect of undermining the sense of trust developed through other aspects of the class.

Again, our co-author's experience:

> I [author Anaelle] rarely experience instructors openly sharing their sentiments regarding artificial intelligence with their students. Instead, my professor's policies are generally explained in syllabus sections dedicated to defining academic integrity violations and/or expectations of students in the course, and at most these may be briefly mentioned on the first day of class. My most engaging and enlightening classes engage in co-creation, where instructors modify learning outcomes to support individual student goals and unique learning approaches. Those same instructors, however, tend to maintain a strict unspoken interdiction of LLMs, indirectly, from my perspective, countering the pedagogical approach in other facets of their class.
>
> A humanities course I took established outcomes that felt satisfying for me and other students. We chose from a meaningful set of options to demonstrate our understanding of class materials by designing a final project, applying field-specific research methods and using novel theoretical perspectives. This represented a higher degree of student involvement when compared to other assessment methods. For example, the use of "Un-Essays" as a measurement of our learning allowed us to choose how we wished to apply class concepts and experiment with various avenues to share research findings. Additionally, assignment deadlines were designed to allow students to track their work, with no penalty for late assignments. In this context, the balance of structure and autonomy created a valued classroom environment that students perceived as co-created with our input used.

This partnership-oriented structure highlighted the glaring omission of a discussion about the possible roles and impact of AI in our work and the field more broadly. I have seen other scholars and professionals using AI tools as part of similar student projects.

However, hoping that student engagement and the joint creation of assignments are enough to discourage AI use does not spur critical engagement with AI. Excluding students from decision-making and setting expectations for the use of AI creates more problems in the future than the temporary relief of avoiding this unfamiliar terrain. Students experience increasing frustration and distrust regarding the practical utility of their coursework and turn to AI when we do not believe in its value. I am confident that exploring and co-constructing the use of AI tools in the classroom will only improve students' and professors' algorithmic literacy by promoting a joint evaluation of AI's strengths, limitations, and capabilities. Regardless of which threshold of engagement with AI an individual maintains (which will have significant variance even across a few scholars), this technology can educate us as much as it can disrupt learning when complimented with honesty, flexibility, and equitable relationships between students and their teachers.

Ladder of Engagement/Co-Creation with Students

We have developed a four-stage pathway of improving engagement that involves increasing levels of trust and responsibility in students concerning AI in the learning environment: 1. Entering; 2. Exploring; 3. Evaluating; and 4. Integrating. While we recognize that when many instructors see progressive frameworks their instinct is to begin at the top, given the need to develop our own critical framework, we think this may not be the best approach in this instance, as co-creation requires significant comfort with uncertainty, willingness to cede institutional authority and trust in students. As an entry point, instructors can model and practice our suggested algorithmic awareness strategies with students to develop a shared ethic around learning with AI.

Entering

In the entering stage, instructors have decided to supersede outright bans of AI, but often are still on their own journey of developing algorithmic awareness. They may also see limited applications in their classes. Instructors in this stage have an initial an understanding of tools in their discipline and as they relate to the class, but often either simplify existing processes related to the discipline. We assume students will generally follow the instructor's demonstrated path unless they have confidence and experience using AI tools. There is little room for exploration on their own, but for many students instructor discouragement of tools is more than they have encountered elsewhere. For instructors, this approach offers the benefit of predictability, which is especially valuable when using tools that are not entirely predictable in their output.

In a hypothetical example, Dr. L, a professor of statistics, has read claims that LLMs would analyze data, generating common outputs like an analysis of variance through textual prompting. She tested this with basic datasets and found outputs that largely did not align with the expected results. Because these incorrect responses lacked any explanation, Dr. L decided to encourage students to avoid using LLMs for most statistical tests. Whereas Dr. L found more value as a study aid for students to find explanations of terminology, and she helped students to create their own study guides and practice tests using LLMs. An LLM approach demonstrates an opportunity to problematize algorithms in disciplinary information interactions with students, empowering them to compare and contrast the effectiveness of these two use cases.

Exploring

In courses that engage with testing of AI tools, instructors push students a little further, accepting that not everything will be inside the instructor's comfort zone. Often these tools are not integrated into all aspects of the course, but in those areas where they are students have more flexibility to explore their capabilities and potential. Instructors may introduce students to a concept from the course along with potentially related AI tools. They might share several ways they have used AI tools in this context, and then invite students to explore on their own (Hellas et al., 2024). Algorithmic literacy pedagogy cultivates a toolkit of inquiry, emphasizing informational context and asking questions - not just memorizing content - as a necessary component for decision-making (Caulfield, 2017). This includes making decisions about whether or when to use AI. Students can explore AI within the disciplinary framework of the course, their discoveries informing the instructor's understanding, but these explorations still take place within a limited scope and do not necessarily translate to other parts of the class or discipline.

In another hypothetical example, Dr. T teaches introductory python coding classes. Many class tasks can be automated through LLM's coding capabilities, but students in the class will generally progress to future classes that demand greater coding skills. Without a strong foundation in these basic skills, students will likely face significant later struggles. While many colleagues use this as an excuse to "ban" LLMs, Dr. T suspects that students will ignore these blanket bans and restrictions. Instead Dr. T develops an assignment where students complete an advanced coding task, explore and reflect where an LLM can help and where it struggles. Dr. T found that students recognized the limitations and discussions indicated that students more fully valued efforts to learn fundamentals.

Evaluating

In courses that actively evaluate AI tools, instructors solicit students' existing experiences with AI and seek to incorporate them into elements of the course. Such an approach requires a balance of the instructor's understanding of potential uses of AI with students' ideas for how AI might contribute to learning. This can involve inviting students to use AI tools to generate study materials and to support assignments that are not AI-specific (e.g., idea generation, outlining, writing support, data analysis). Collaboratively develop algorithmic literacy by integrating reflective exercises into coursework to examine our perception of a source's accuracy or trustworthiness (Oeldorf-Hirsch & Neubaum, 2023). The instructor cedes a reasonable amount of control, encouraging students to use AI tools as they deem appropriate. There exists a clear structure for students to share with the class their findings regarding the value and use of AI tools.

In another hypothetical, an instructor teaching technical writing has heard from many students about their use of Grammarly, a spelling/grammar checker tool spelling/grammar checker that also utilizes LLM technology. In response, Dr. Q incorporates elements throughout the class where students experiment with current LLM models and determine what benefits they might have for particular technical writing contexts, and where they may be less useful. Dr. Q has personally found that LLMs could facilitate navigation of complicated texts and simplify language, but also consistently made errors that required professional experience to correct. For Dr. Q, who has a decade of professional writing experience, LLMs were not particularly beneficial. Dr. Q hoped that these tools could allow students to overcome an initial challenge of not knowing where to start drafting or finding sources, even if the content generated was not always well-constructed or useful.

Integrating

In courses that co-create their use of AI tools, instructors begin with open discussions about what AI tools might look like in the class and how they might be used, documented, and explored (Zheng et al., 2024). The aim is for the students to guide the discussion with input, but not necessarily direction from the instructor. It can be valuable to create structures that offer students different levels of engagement, including students who may decline to engage with AI tools for ethical or moral reasons. The core goal of combining algorithmic literacy practices and pedagogical partnership is to prepare students to meet the world's complex questions and varied perspectives with curiosity, open-mindedness, and, most importantly, conviction that their actions matter. Partnership-oriented algorithmic literacy creates opportunities for 'transformative action'—collaborative, participatory learning experiences with real-world connections, in which students apply learning to shape their courses, work places, or other communities.

Our co-author's experience:

> I [author Anaelle] participated in a faculty learning community supported by student partnership. This program connected students and instructors to share perspectives and co-create curricular plans to address ideas or challenges associated with implementing AI in the classroom. Though the purpose of the learning community was to design strategies that embodied the algorithmic literacy framework, the goals of each instructor varied greatly. I noticed a tendency for educators to present preconceived projects to the student partners and gather feedback to improve the course design's relevance and efficiency, which left some students feeling unsatisfied in their ability to contribute directly to the projects. Together, me and my partner determined a course structure that would explore different facets of AI in the instructor's respective field, ultimately guiding students to engage with AI critically and ethically.
>
> Partnerships that closely studied and incorporated algorithmic literacy together in their learning outcomes were most successful, despite instances in which members held opposing views and understandings of AI. I expect that incorporating AI co-creation in classrooms will face obstacles as both parties navigate a new level of student engagement. Instructors may fail to honor students-as-partners pedagogy by maintaining students as sources of feedback instead of productive collaborators; students may be wary of working with instructors on a topic they may not understand in depth. Thus, the expectations of the student-instructor partnership must be made clear from the earliest stages to guide students and instructors in this unconventional scholarly process.

The Toolbox of AI Co-Creation

This paper serves primarily as a call to attention and hopefully action, which we hope will lead to more significant developments and strategies that are discipline-specific as well as crossdisciplinary as we grapple with higher education in the age of generative AI. Here we seek to open this discussion with some strategies and resources we have used successfully.

Pre-course Surveys

Student perspectives remain a vastly underutilized resource throughout teaching in higher education. We highly encourage pre-semester surveys for many reasons as part of a co-created learning environment, and including at least one question about AI usage can provide valuable information about your students. Potential questions can focus on student experiences with AI, student desires or non-desire to learn about AI in the context of the class topic/discipline, and even student preferences about policy. Having planned thoughts about AI tools helps with contextualizing and explaining a policy (even a predetermined one), and in the best instances can help facilitate a conversation about co-created policies, especially since AI is a topic that students associate with academic dishonesty and may initially be unwilling to discuss openly.

Example Assignments

In [Author Dan]'s course on the history of rock music he wanted students to explore how AI might be used in the creation of music. Because emerging generative AI audio tools are too complicated for students who largely have no musical background, he turned to song lyrics. For many students lyrics are a central part of the appeal of many of their favorite songs, so he invited students to use LLMs to generate lyrics for a new song of their own design. Some still chose to write lyrics on their own, but many experimented with different ways to generate lyrics from different inputs or worked from an initial output to edit the lyrics based on their desires. Students recognized one way these tools could be used to save significant time. Students also identified some limitations, like how ChatGPT tends to emphasize certain rhyme schemes when instructed to write lyrics or tends toward explicit imagery. We believe the effectiveness of this task was enhanced because the course followed a student-reflection-based ungrading scheme. These individual assignments were not graded on instructor-set criteria, but rather students were asked to reflect on their takeaways from the activity and responses to others' generated songs.

Example Explanations

Developing one's own AI literacy becomes particularly important when providing explanations and examples of uses in the class and what these tools will potentially be helpful for. In [Author Dan]'s rock history course, students complete a number of unessays, picking a topic and presenting to peers. Since this is an online class, and he allows students to use AI tools to contribute to their work, he sought to demonstrate ways students might find them most valuable through a video with specific examples. In the video he entered prompts that reflect some common student usage cases. One involved asking for assistance with generating topic ideas ("what are some example topics for a presentation on female rock musicians in the 1960s") which generated numerous usable suggestions. Another asked for specifics about a band ("give me a timeline of the history of Black Sabbath"), which as pointed out in the video, gave a mostly thorough timeline, but included one significant error. He suggested Wikipedia provided a better, more thorough, and more accurate resource for this question.

Considerations and Hesitancy with Regard to Co-creation

Many faculty and faculty developers express initial hesitation with regard to engaging students in co-creation processes. These fears and concerns, we believe, are often rooted in a perspective of education that places instructors and students in opposition. While teaching practices over the past two decades have pushed instructors to create more engaged and collaborative learning environments, fears about LLMs have recently reignited oppositional views. As we co-write this paper in an off-campus cafe near our university we overheard a group of four instructors discussing strategies for challenging students they perceived to be using ChatGPT (such as asking them on the spot to give an oral three-minute overview of their paper). We believe that taking this oppositional perspective to the co-creation space will result in unsuccessful and likely faux-created environments. Co-creation can also interfere with some approaches to the process. Those who approach the course design process ahead of time will often find that the students in the class will interfere with or not conform to an idealized vision of how the class might proceed. Thus, successful co-creation requires a real-time process orientation where there are opportunities to deviate from even well-constructed plans.

When collaborating in partnership, we need to recognize, emphasize, and honor different perspectives, values, experiences, and expectations among the variety of students in a class. Many instructors initially explore co-creation through systems that reflect democratic decision-making using either majority-rule or structures based around building consensus. These structures pose particular challenges in campus environments where complicated power hierarchies and social environments lead to differing levels of comfort among students speaking out about their opinions and perspectives, especially regarding controversial topics like LLMs and AI. We need to take caution when engaging students in these discussions to ensure that some students are not silent out of fear (we also do not want to force students to speak). Building on this, we need to be cautious about decision-making processes. While it might be tempting to have a vote (whether public or private) and follow the results of that vote, this can lead to feelings of alienation when some students feel that their opinions were invited then summarily dismissed. This is especially true when some students have social and political objections to LLM usage (ecological costs, human tolls through the traumatic and underpaid labor of Kenyan workers, etc.). Much as we would provide food options to meet the needs of students who are vegetarian, we also think it is important to follow up discussions with possibilities and opportunities for students who have different perspectives on the use and social value of LLMs.

Bringing Algorithmic Literacy Pedagogy Together: Practice Four—Transformative Action

As information and knowledge creation processes are, in some ways, increasingly democratized, education's purpose must shift to preparing students to engage in their own knowledge building. This means moving beyond the economic calculus prioritizing the rote development of skills for joining the workforce, toward transformative education that engages students' whole selves in critical dialogue, working toward social justice and civic engagement, no matter their academic field or future profession. However, the hope of AI tools democratizing knowledge is complicated by the fact that a handful of powerful corporations control leading AI technologies, and human bias ingrained into the creation of these tools can limit how people are able to create, innovate, and think critically as the ubiquitous integration of AI systematizes racism, sexism, and ableism (Noble, 2018).

The collective development of algorithmic literacy in pedagogical partnership is one answer to the challenges AI poses to the democratization of knowledge and education. Algorithmic literacy pedagogical practices can help us move toward transformative social action as a core outcome of education:

> When information literacy instruction teaches students to become consumers of information, it upholds an individualistic and human capital oriented status quo. Unless actively questioning the goals of many recent educational technology interventions…constant disruptions of innovation thus detract from any kind of reflective, critical praxis of teaching and deprive students of the skills necessary to build knowledge that is used to create liberatory information and action for social change. (Espinel & Tewell, 2023)

Rather than making a unilateral or inflexible decision about when and why to use AI in your course, collaboratively develop your course AI policy with your students. This can create an opportunity for students to take ownership of their own learning outcomes as they consider how AI might positively or negatively affect their ability to learn what they want to learn. Consider ways that you might feature student work as examples, documentation, or study materials for future students. For example, students can document and share individual AI prompting experiences as guidance for other students learning to use AI productively.

Approaches to integrating transformative action could include: asking students to create examples or documentation that will support future students in the use of AI for learning; replacing a final exam with an experiential or service learning project to create an AI tool that benefits a community; engaging a negotiated curriculum, where students help determine when and why AI can be used, and can even lead discussion around a disciplinary use of AI. When our teaching and learning culminates in taking pro-social action to improve the world around us, it requires both instructors and students to draw on unique personal experiences and strategies for "real world" information evaluation. It creates opportunities for collaboration and learning from one another as we encounter new types of information and practice new skills.

Adopting a process orientation in your classrooms develops the skills to contextualize information and identify how that information can be used reliably. Adopting inquiry-based learning in your classroom fosters a critical mindset toward learning with algorithmically-mediated information. These approaches bridge in-class and out-of-class information practices by inviting students to apply prior knowledge they bring from unique experiences to their work in class. Students frequently use algorithmic social media platforms and have already developed skills and strategies for evaluating information and communicating ideas tailored to a particular audience (Head, Fister & MacMillan 2020).

The overarching goal of combining algorithmic literacy and pedagogical partnership is to cultivate education for democracy - to prepare students to meet the world's complex questions and varied perspectives with curiosity, open-mindedness, and a belief that their actions make a difference. Algorithmic literacy approaches create opportunities for 'transformative action' - collaborative, participatory learning experiences with real-world connections, which lead to taking action that challenges or improves the status quo. Students, like all of us, want to contribute their strengths and be challenged to do work that matters to others. Transformative action builds on the approaches mentioned earlier to create a learning environment where students view their course work as a vehicle to actively improve the world around them with their own ideas.

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