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# Expanding AI Literacy: How Emotional Intelligence Supports Productive Uncertainty

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**Abstract**

This paper presents a conceptual framework for understanding the role of uncertainty in the context of LLM usage in education. We argue that AI does not eliminate uncertainty but displaces it, often reducing epistemic uncertainty while amplifying forms of uncertainty experienced at the level of metacognitive and emotional engagement. Throughout the paper, we use hypothetical examples to illustrate the theoretical concepts discussed, although these examples are not meant to provide a predictive account of student outcomes. Finally, we present emotional intelligence skills as a vital but often-overlooked component of AI literacy, helping students recognize the uncertainty that arises in co-creation with LLMs not as a cause for unproductive anxiety, but as a catalyst for creativity.

**Keywords:** uncertainty, emotional intelligence, self-efficacy, AI literacy, metacognition

## 1. Introduction

The entrance of artificial intelligence into the public discourse has introduced many levels of uncertainty. While various industries move rapidly to unveil AI initiatives, nobody can say definitively how this new technology will affect these sectors long-term, how human capabilities will shift as AI use becomes standardized, or even how the technology works. Developers and researchers openly acknowledge limits in their ability to explain why AI makes one choice instead of another or why reliability varies from one case to the next.

Despite all this uncertainty regarding AI, the technology itself suffers from no such affliction. Responses from popular LLMs (GPT-4o, Claude, Gemini, etc.) have been characterized as "highly sycophantic" [1, p.7], confidently affirming users much more frequently than expected and potentially steering them toward unfounded conclusions [2]. These challenges take on particular significance in education, where managing uncertainty already plays a key role in learning. In AI-mediated learning, when an LLM presents every answer with authoritative confidence, students are left to evaluate these answers alone while facing uncertainty the system does not recognize.

This paper contributes a conceptual framework for understanding how AI reshapes students' experiences of uncertainty. In much of the existing AI literacy literature, uncertainty is implicitly framed in one of two ways. First, uncertainty is treated as epistemic noise: a form of error, ambiguity, or informational instability that interferes with knowledge acquisition and should be minimized through improved system design, clearer prompts, or stronger evaluation mechanisms—for example, by reducing hallucinations, increasing factual accuracy, or training students to elicit more reliable outputs. Second, uncertainty is framed as an emotional risk: a source of anxiety, discomfort, or reduced self-efficacy that must be regulated in order to protect learner confidence and performance, as when instructional guidance emphasizes reassurance, affective safety, or confidence-building strategies in AI-mediated tasks. In both cases, uncertainty is positioned as a deficit—either cognitive or affective—rather than as a constitutive condition of judgment and learning.

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This paper departs from both framings by treating uncertainty as differentiated and redistributed rather than eliminated. We argue that AI systems selectively reduce epistemic uncertainty while intensifying metacognitive and emotional forms of uncertainty that are less visible but pedagogically consequential, particularly those related to judgment, agency, and authorship. From this perspective, AI does not resolve uncertainty but displaces it across domains in ways that can feel supportive while undermining learning over time. We further argue that emotional intelligence functions as a critical but underdeveloped component of AI literacy, enabling learners to recognize and regulate these redistributed uncertainties so that they remain generative rather than anxiety-inducing in AI-mediated knowledge production.

## 2. The Role of Uncertainty in Education

Uncertainty can be described in several ways within the field of education, but one classification is particularly relevant in the context of AI: epistemic uncertainty. Epistemic uncertainty is situated within the idea that learning something new inherently forces the learner to question and revise their existing beliefs [3]. Yet epistemic uncertainty never appears alone. It is accompanied by uncertainty about how one's work will be evaluated, uncertainty about one's own judgment and interpretive adequacy, uncertainty as a felt emotional state, and uncertainty about how to express ideas appropriately within social and institutional contexts. These forms of uncertainty are analytically separable but practically entangled, shaping how learners interpret challenge, feedback, difficulty, and risk. This matters because AI systems often appear to help learning by reducing uncertainty, while quietly shifting uncertainty into forms that are harder for students to recognize and manage, particularly uncertainty about judgment, agency, and authorship. Within an educational system, students' experiences of these academic uncertainties may be shaped by assessment practices, feedback structures, and even classroom dynamics.

Educational research often approaches learners' engagement with uncertainty through the concept of metacognition, understood as the capacity to monitor and evaluate one's own thinking. This framework captures important aspects of reflection, self-assessment, and regulation as they occur within the learner's experience. In this paper, we retain this term to describe these processes. At the same time, we distinguish it from intracognition, which designates the conditions under which such evaluation unfolds in AI-mediated contexts. Intracognition refers to the distributed, recursive activity through which interpretation, response, and revision emerge across interaction with technical systems. Metacognition describes how learners engage their thinking; intracognition describes how that engagement is shaped, extended, and reorganized within the exchange itself.

In the interest of promoting deep learning for their students, some teachers may use "lesson unplanning" [4, p.1] to not only manage uncertainty in their classrooms, but to actively encourage it. This pedagogical method requires students to think through problems creatively, while the teacher resists providing a constrained set of "correct" answers or guidelines for the final products. For example, rather than asking students to write a five-paragraph essay about character development in The Great Gatsby, a teacher could give the students freedom to choose how they want to create a representation of the characters. We will return to more hypothetical examples shortly to discuss how introducing AI in the classroom complicates this task.

Of course, there's a fine line between fostering uncertainty in the classroom and neglecting to give students the structure they need to succeed. An effective model for deep learning includes raising uncertainty (helping students identify what they know and don't know about a topic), maintaining it (encouraging students to dig deeper and discuss with others), and ultimately reducing it by guiding students to robust understanding [5]. As Scherer et al. [6]

note, "education has always lived in tension [between] assuring continuity and... fostering creativity and change" (p. 3).

This tension should also be considered in relation to what Bandura [7] describes as mediating beliefs related to perceived self-efficacy, or "the strength of people's convictions in their own effectiveness" (p. 193). In his later research [8], he explores the relationship between anxiety and self-efficacy, noting that when individuals do not feel confident before a task, they "rouse themselves to elevated levels of anxiety that far exceed the fear experienced during the actual threatening situation" (p. 212), making it less likely that they will succeed on the task itself.

Essentially, self-efficacy and anxiety operate in a recursive loop: Feeling anxiety often affects a learner's performance, which then convinces them they do not have what it takes to succeed, which lowers their self-efficacy, which increases their anxiety in the future.

Conversely, learners with high self-efficacy are more likely to respond to uncertainty as an opportunity for creativity. In fact, tolerance for uncertainty is frequently associated with more creative personalities [9].

In other words, students do not simply respond to uncertainty as a situational condition. They interpret uncertainty through metacognitive beliefs about their own capacity to act effectively, persist through difficulty, and exercise judgment in the face of ambiguity. Perceived self-efficacy shapes whether uncertainty is experienced as a manageable challenge or as a signal of impending failure, and whether external feedback is taken up as guidance, threat, or confirmation of inadequacy.

## 3. How AI Both Erases and Creates Uncertainty for Students

The introduction of AI into learning environments complicates this landscape by redistributing uncertainty across these domains rather than resolving it outright. AI systems may reduce epistemic uncertainty in some tasks while simultaneously intensifying forms of uncertainty that are often experienced as metacognitive and emotional within AI-mediated interaction, leaving students to manage forms of uncertainty the system itself may not register. Educational research has yet to adequately account for this redistribution, often treating uncertainty that arises from interacting with AI tools either as a cognitive deficit to be minimized or as an affective obstacle to be regulated. Clarifying how different forms of uncertainty are displaced, transformed, or amplified in AI-mediated learning therefore represents a critical and underexplored problem for AI literacy research— one that calls for conceptual modeling as a necessary precursor to empirical investigation.

The problem, then, is not uncertainty per se, but that AI reorganizes which kinds of uncertainty students experience while educational research lacks a sufficiently differentiated vocabulary for tracking this redistribution. In the remaining sections of this paper, we develop conceptual models that trace how distinct forms of uncertainty emerge in AI-mediated learning and how current approaches to AI literacy fail to address these dynamics. The aim is not to predict learner outcomes, but to identify structural gaps in existing AI literacy frameworks.

### 3.1. A Framework for Redistributed Uncertainty in AI-Mediated Learning

To make this redistribution analytically tractable, we propose a framework that differentiates uncertainty across five interrelated domains:

(1) Epistemic uncertainty, referring to uncertainty about the correctness, completeness, or reliability of information.
(2) Evaluative uncertainty, referring to uncertainty about standards, adequacy, and how work will be judged.

(3) Metacognitive uncertainty, referring to uncertainty about how to act on, revise, or integrate AI-generated outputs as these processes are experienced by the learner within ongoing interaction.
(4) Emotional uncertainty, referring to affective states such as anxiety, confidence, or unease that shape persistence and risk-taking.
(5) Communicative uncertainty, referring to uncertainty about authorship, voice, expression, and responsibility in AI-mediated production.

## 4. **Conceptual Models**

As noted, introducing AI into the learning environment complicates the role of uncertainty. On the surface, LLMs and other AI tools may appear to erase uncertainty altogether. A student looking for the answer to a math equation or a bulleted synopsis of a book will quickly find the answer they're looking for from an LLM, presented in perfectly polished prose projecting the confidence of an expert voice. This model of interacting with AI has been termed the "vending machine pipeline" [10], treating information like a commodity the LLM already possesses, awaiting retrieval like a bag of Doritos by a hungry student who just pressed B4.

When a student is operating from a place of low self-efficacy, the vending machine pipeline provides relief from epistemic and evaluative uncertainty to an extent, supporting the learner's ability to engage and respond within the task. Think of the international university student who wants to translate an email to her professor into her second language, or the 7th grader trying to remember the steps of the cell cycle. In both cases, these students are not confident in their own ability or recall, and thus they rely on the correctness of the LLM's response. For simpler tasks like these, an LLM probably is sufficient to meet the students' requests.

It's in the word "probably" (itself a hallmark of uncertainty), however, where issues start to emerge with the vending-machine pipeline. Research conducted in the workplace [11] suggests that AI's impact on employee creativity is mediated by metacognitive skills as these are enacted through ongoing interaction with AI-generated outputs. Employees with high metacognitive strategies were more likely to analyze responses from an LLM, revise an LLM's suggested solution, and track its effectiveness for further revisions. In turn, this AI-assisted workflow significantly increased employees' creativity. On the other hand, employees with low metacognitive strategies were more likely to accept whatever input the AI provided rather than challenging it. Although this study focuses on workplace settings, its findings on metacognition can be extrapolated to educational contexts as well. This finding illustrates a key problem with the vending-machine pipeline [10].

Thus, the central issue with using AI in education is that students may use this technology as a quick fix for their uncertainty rather than to sit with it, investigate further, and learn more deeply. Returning to the "lesson unplanning" example [4] where a teacher gives students creative freedom over how to display their content knowledge of The Great Gatsby, this task 4 is not quite as well-suited to the vending-machine pipeline. Seeking help from an LLM on a task like this is likely to result in a list of generic ideas of varying usefulness and feasibility. When a student has ceded their judgment to this tool, they may view this list as the "gold source" of the best ideas, meaning they're likely to just take one of these ideas and run with it.

By not applying their metacognitive skills, they may experience a decrease in their self-efficacy. Because the student doesn't have an intellectual investment in the initial idea proposed by the LLM, they may experience frustration as they try to cobble together the project because "ChatGPT said it was a good idea." This pathway leads to the unproductive, anxiety-inducing uncertainty described by Bandura [8]. In other words, the introduction of

AI does not eliminate the student's uncertainty; it shifts uncertainty from questions of correctness ("I don't know the answer") toward questions of how to engage, interpret, and act on AI-generated outputs within ongoing interaction ("I don't know what to do with this answer").

To tap into the productive uncertainty that fosters creativity and learning, students need a mindset shift, viewing AI not as a vending machine but as an intellectual co-creator. Matson refers to this idea as the cognitive intraface [12], "the recursive zone where embodied and technical cognition meet as co-constitutive processes...Meaning arises in their continual negotiation, where neither determines the other but each conditions the other's interpretive relation."

In other words, the student works alongside the LLM, understanding and appreciating that their human skills and the technical skills of an LLM are not the same, nor should anyone expect them to be. Both "agents" (the student and the AI tool) possess unique capacities that add value to the cognitive intraface, "opening new possibilities of thought and action, producing ideas and associations that neither human nor machine could have mustered alone" [10].

## 5. **Practical Applications for Education**

Many lessons promoting AI literacy tend to focus on critical thinking skills and evaluating AI responses for bias [13]. While both remain important, their emphasis at early stages can misdirect attention. When students have not yet developed the capacity to remain engaged within conditions of uncertainty, instruction that foregrounds bias detection can intensify unease in ways that inhibit judgment, producing forms of vigilance that register as anxiety rather than inquiry.

A different orientation begins with how uncertainty is experienced and interpreted. Emotional intelligence frameworks [14] provide one entry point by offering terms for recognizing and articulating affective states as they arise. The RULER framework [15]—recognizing, understanding, labeling, expressing, and regulating emotions—can be situated within AI-mediated dialogue as a way of sustaining engagement with uncertainty without requiring its immediate resolution.

To illustrate this dynamic within the cognitive intraface [12], consider a student working on a "lesson unplanning" task [4] using an LLM to explore possibilities for representing her understanding of The Great Gatsby. The model produces a familiar set of options: diary entries, a mock trial, a character-based playlist. These responses exhibit recognizable academic forms and carry a sense of immediate usability.

The student experiences a sense of unease in relation to this list. The unease does not immediately resolve into a clear understanding of what is lacking. It remains ambiguous in its object. At moments, it appears to concern the usefulness of the ideas; at others, their fit with the assignment, or her own capacity to execute them. As she begins to articulate this unease within the exchange, the model responds to elements of her language—hesitation, qualification, partial evaluation—by prompting elaboration. Dialogic interaction does not lead to feedback in a linear or transactional way. It gives rise to an emergent and shifting sense of what the uncertainty in this context might be about. The exchange produces a series of partial interpretations, none of which fully resolve the situation, while each reorients how the student encounters the available options.

As the student revisits the list, her evaluation proceeds unevenly. The mock trial appears logistically impractical. The diary format introduces concerns about execution. The playlist retains some interest, though it carries uncertainty about adequacy within the expectations of the assignment. These determinations narrow the field without stabilizing its direction.

At this point, a different line of thought begins to take shape. The student recalls a scene involving music and considers how the characters' interactions might be understood through a musical structure. The idea does not present itself with clarity or assurance. Its status remains uncertain, introducing questions about interpretation, representation, and evaluation that extend beyond the initial set of options. The student brings this emerging idea back into dialogue with the model, which extends it through additional suggestions without establishing its validity. The exchange continues under conditions in which the value of the idea remains open. Uncertainty in this exchange reflects more than a lack of clarity or confidence. It functions as a signal that the student is moving beyond familiar or easily validated interpretations toward less familiar, higher-risk conceptual territory. In this sense, uncertainty marks a deviation from dominant interpretive pathways and becomes an indicator of intellectual risk.

Registering this uncertainty involves an intracognitive dialogue with the model in which the student attempts to interpret what the uncertainty signifies and how to act in relation to it. This process unfolds across heterogeneous forms of cognition. The model operates through nonconscious cognition as context-specific probabilistic selection, generating responses through patterned sensitivity to linguistic cues—including tone, verbal indicators of hesitation, and evaluative language—without access to affective or embodied states as lived experience. In this capacity, the model registers and responds to potential linguistic markers of uncertainty or anxiety, reintroducing them into the exchange as structured prompts, reframings, or suggestions. The student engages through nonconscious embodied cognition, where feelings such as anxiety, hesitation, or attraction to an idea register pre-reflective interpretations of relevance and risk.

It's important to note that the above example is not meant to be prescriptive or predictive, suggesting that all students will have this exact experience, as of course we know that's not the case. Rather, this example demonstrates the potential ways in which these distinct cognitive processes intersect through ongoing exchange within the cognitive intraface. Uncertainty emerges as an embodied signal that organizes how the student navigates and evaluates the model's outputs. Its generativity depends on the student's capacity to interpret these signals as indicators of intellectual risk and to sustain engagement with them long enough for new interpretive pathways to develop. The significance of these signals is not established through the model's recognition alone. It is established through the student's ongoing evaluation of whether the model's responses correspond to or misread her embodied experience. This recursive movement across affective and reflective registers constitutes intracognition within AI-mediated dialogue.

In this way, the cognitive intraface [12] provides a unifying lens for the processes described throughout this paper. Metacognitive evaluation [11], as enacted within the exchange, alongside perceived self-efficacy [7, 8] and emotional intelligence [15], operates within a shared field in which uncertainty remains active as a condition of learning. Instructional support, then, involves developing students' capacity to remain engaged within these conditions, recognizing uncertainty as a signal of intellectual risk and sustaining it as part of the process through which new interpretive pathways become available. Integrating the cognitive intraface into AI literacy curricula offers one approach to supporting this form of engagement.

## 6. **Practical Applications for AI System Design**

To integrate the cognitive intraface directly into LLM design, models shift from a Socratic tutor model toward a dialogic, inquiry-based form of interaction that engages academic content alongside the broader conditions under which that content is encountered. This includes attention to affective and interpretive dimensions such as uncertainty, hesitation, and perceived difficulty as they arise within exchange. These dimensions remain within dialogue

as elements that can be articulated, interpreted, and revised over time, rather than being translated into metric abstractions or quantitative indicators that stabilize interpretation prematurely.

Within this framework, feedback operates as a form of intervention that sustains engagement with uncertainty. It prompts elaboration, responds to partial or tentative evaluations, and supports the development of multiple possible directions of thought, allowing interpretive movement to continue without convergence on a single authoritative path. The learner participates in this process by contributing their own interpretations of the situation, including expressions of difficulty, uncertainty, or resistance. These expressions enter the exchange as meaningful components that shape how the interaction unfolds and how the task is encountered. These dynamics reconfigure how agency is distributed within AI-mediated learning. Interaction becomes a site in which evaluation emerges through exchange, with the learner engaging ongoing interpretations of their capacity to continue under conditions that remain unresolved. Perceived self-efficacy, in the sense described by Bandura [7], emerges within this process as part of that interpretive activity.

Intracognition, as introduced earlier, describes the distributed and recursive conditions under which these processes take place. Reflection unfolds through interaction, with the system registering patterns in language—such as hesitation, qualification, or shifts in evaluation—and reintroducing them into the exchange as prompts for further articulation. These responses remain tied to linguistic expression, allowing the learner to evaluate whether the system's interpretation corresponds to or misreads their experience, without presuming access to affective or embodied states.

This approach aligns with ongoing work with TrekAI, an educational technology company based in Atlanta, Georgia, in which dialogic interaction functions as the primary interface for engaging the conditions that shape learning. The system maintains provisional accounts of learner experience that remain open to revision over time. Expressions of uncertainty, avoidance, or difficulty function as structured inputs that inform interpretation across interaction, without being reduced to stable traits or singular explanations. From this perspective, AI system design sustains the conditions under which uncertainty functions as a signal of intellectual risk. Here, interaction supports continued engagement with interpretive processes that extend beyond familiar or easily validated forms, allowing meaning to develop through ongoing exchange.

## 7. Conclusion

This paper charts the role of uncertainty in education and its unique ability to push students toward unproductive anxiety or productive creativity, particularly when working with artificial intelligence. While treating AI as a vending machine may resolve epistemic uncertainty for simple tasks where students lack self-efficacy, overreliance on AI when approaching complex tasks is likely to further damage students' self-efficacy and lead to anxiety. Significant empirical work is needed to examine how these dynamics manifest across contexts, task types, and student populations. This paper demonstrates how the anxiety that forms as a result of low self-efficacy in AI interactions may be mitigated by teaching students how to engage AI as a co-creative force in a cognitive intraface. However, this level of engagement requires a high degree of emotional intelligence. Thus, our argument positions emotional intelligence as a missing but essential component of AI literacy, enabling students to transform uncertainty from a roadblock into a springboard for creativity.

In this context, the central problem for AI literacy is not whether AI reduces uncertainty, but which forms of uncertainty are reduced, which are intensified, and how those shifts affect learners' ability to sustain productive engagement. Uncertainty becomes unproductive not because it exists, but because it crosses thresholds within specific domains—particularly

metacognitive and emotional ones—where judgment collapses and authority is substituted rather than exercised. Emotional intelligence frameworks enter this model not as solutions that eliminate uncertainty, but as regulatory supports that help learners recognize affective signals, manage escalation, and remain within productive thresholds long enough for judgment to remain active.

The contribution of this framework, then, is diagnostic. It reframes AI literacy as the capacity to recognize how uncertainty is redistributed across epistemic, evaluative, metacognitive, emotional, and communicative domains, and to sustain those uncertainties within productive bounds in the presence of systems that project confidence while remaining opaque about their own uncertain status. By articulating uncertainty in this differentiated way, the framework clarifies why existing research often fails to capture the lived dynamics of AI-mediated learning and why new empirical work must attend not only to academic outcomes, but to intracognitive negotiations with LLMs, including metacognitive evaluation, mediating beliefs, and affective experience over time. By treating uncertainty as differentiated and redistributed rather than simply reduced, this framework explains why AI can feel supportive while undermining learning, and why AI literacy must be understood as a capacity for judgment under uncertainty rather than a set of technical skills.


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