Extending the Expert Learner Framework for Co-Regulation with GenAI

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Abstract

The rapid advancement of generative artificial intelligence (GenAI) has intensified the need for understanding, using, and critically evaluating GenAI systems. This has contributed to an increase in initiatives integrating GenAI into education, primarily focusing on technical competence rather than reflective understanding of its use. As the deep learning algorithms that power these GenAI tools continuously improve their performance, so too must the deep learning of the human learner. Reflection has long been recognized as integral to deep learning as a process through which learners can make sense of experiences, connect theory to practice, and develop informed perspectives within a discipline. This paper addresses this gap by proposing a reflective framework to support students in critically examining their metacognitive processes as they are exposed to the fast, immediate, and seemingly accurate GenAI outputs during their learning processes. Grounded in the Expert Learner Model, the extended framework aims to support students to move beyond surface-level reliance and trust of GenAI outputs toward critical engagement with GenAI technologies. In doing so, the framework seeks to support students to learn and use metacognitive strategies for ethical and responsible participation in an AI-driven world.

Introduction

The rapid advancement of artificial intelligence has created a growing demand for AI literacy, broadly defined as the capacity to understand, use, and critically evaluate AI systems [1], [2]. This demand impacts students in higher education as they are a key audience in developing AI literacy and will likely need these skills in their careers [2], [3], [4]. In response to the demand, global initiatives have sought to integrate AI within education, [4], [5], [6] yet research has begun to identify that students often only have a foundational or fragmented understanding of AI [7], [8], [9] largely focused on technical skills [10]. While AI literacy skills are important, researchers argue that learning must also extend beyond literacy of the tools and include ethical reflection [11], [12].

Reflection is a process where individuals consider their experiences, think through possibilities, and build informed opinions about a topic [13]. While reflection is viewed as an important part of the learning process, higher education often focuses on technical knowledge and procedural skills within a discipline rather than self-awareness and critical inquiry [14], [15]. Subsequently, there remains a limited understanding of how best to teach and support critical reflection in higher education, including the challenges and practicalities involved [16], [17].

Building on prior work that has identified the need for educational approaches to actively engage learners in critically examining GenAI's broader implications, we propose a reflective framework that can be used as a tool to support students' engagement with GenAI. Recent research has shifted attention from using GenAI as a reflective tool to reflection on GenAI itself, encouraging students to question the ethical, social, and personal implications of GenAI technologies [11], [18]. Therefore, we have focused on extending a reflective framework building on the expert learner model by Ertmer and Newby [19]. Our framework aims to guide instructors in supporting students to move from surface awareness of GenAI tools toward critical evaluation of its outputs and the associated learning process, with the overarching goal of developing reflective practices on its use, limitations, and impacts.

Review of the Literature

AI and GenAI Context

Artificial intelligence (AI) applications are becoming increasingly prevalent, driven by using AI for search results and overall reliance on digital tools. In everyday life, people routinely interact with AI through technologies such as customer service chatbots, search engine algorithms, and use it as a smart assistant [20]. AI is influencing workplaces [21] and educational institutions [22], and the ubiquity of AI identifies the importance of supporting an AI literate population [23]. In particular, students in higher education are a target audience to develop AI literacy, as they will most likely need the skills to use AI effectively in their careers [2], [3], [4]. However, the current state of AI literacy skills among university students remains unclear [7], [8], [9]. In most research, AI literacy and AI in general refers to generative AI (referred to as GenAI from here on) which are computational techniques that can generate seemingly new content such as text, images, or audio from data [20], [24]. In this context, GenAI refers to tools such as ChatGPT, Copilot, Gemini, and other commonly used large language models (LLMs).

In addition, in recognizing the importance of AI education from an early age, educators and policymakers have begun implementing initiatives and curricula to develop AI literacy among K-12 students [1], [2]. For example, UNESCOs updated Digicomp framework 2.2 [6], AI4K12 five big ideas to develop AI literacy in the United States [5], and Sweden too, have included content about AI teaching and learning in their new national K-12 curriculum [25]. Yet, these programs have not yet resulted in a deep or widespread understanding of AI among teachers or students [26]. These findings suggest that, from K-12 to university, current approaches in AI education often fall short, focusing on procedural knowledge rather than supporting critical, reflective engagement with AI. A key factor is that the current literacy approach insufficiently addresses AI-related issues [27], [28] and places the onus on the user to adapt their behavior toward safe practices, rather than encouraging a more critical and reflective stance toward data-driven systems [27].

Given these findings, researchers have argued that AI education needs to go beyond literacy and help support the development of ethical reflection [11], [12]. To address this gap, several studies have introduced reflection-based approaches to understanding technology and AI. For example, prior research [29] investigated the use of reflective journals, requiring students to articulate and analyze their patterns of technology use to understand algorithms. Koenig [29] argued that by doing this, students gained critical and rhetorical understanding of their engagement with technology. Another study [13] explored students' thoughts, perceptions, and experiences with AI through weekly reflective journal entries over six weeks. The findings showed that formal course engagement was important for building AI literacy, but collaboration and real-world interactions also played a key role.

There is also an argument for the integration of ethics into AI education and the subsequent development of valid assessments to evaluate people's capacity for ethical reflection of AI [11]. While previous work has used measurement scales that incorporate elements of ethical reflection, they have predominantly focused on general awareness of AI ethics. Furthermore, some measurement scales have been criticized for primarily focusing on individuals' basic knowledge of AI and its practical application [30], [31] rather than an understanding and reflection of AI use. However, very recently, researchers [18] developed and validated the AI Ethical Reflection Scale (AIERS) to measure university students' capacity for ethical reflection on AI, addressing a gap in existing assessment tools. Broad findings showed that while students can recognize AI-related ethical issues, they are less skilled at critically assessing AI outputs and applying AI for the benefit of society.

Reflection and Models of Reflective Practice

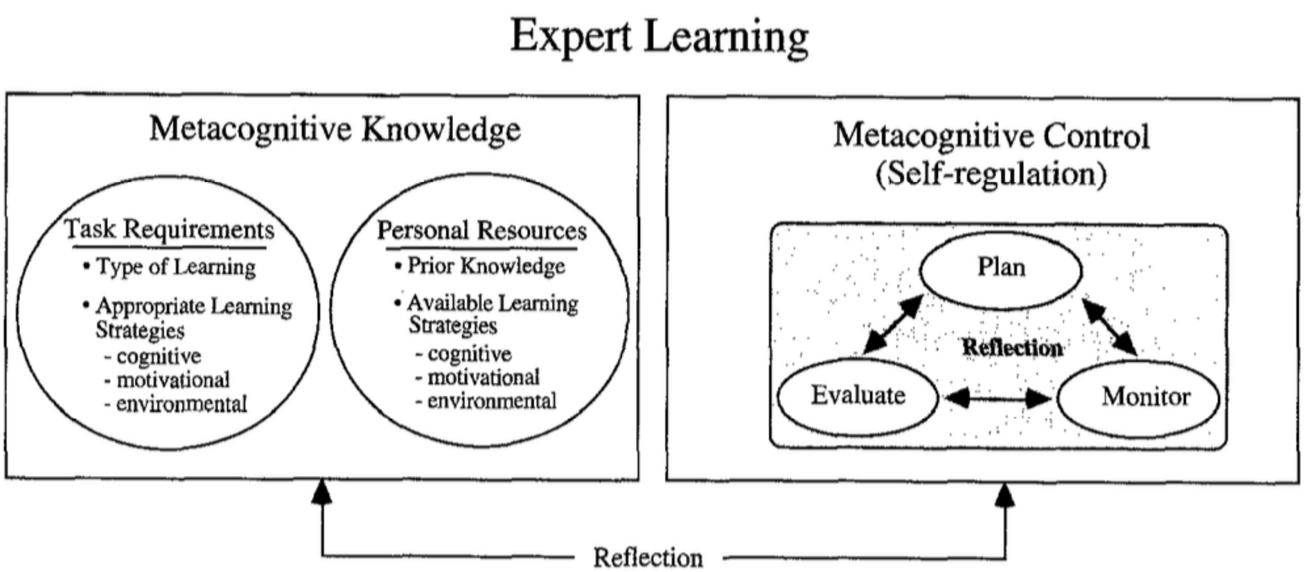
Reflection is thought to begin with asking questions that describe the experience [30]. From this, a second phase occurs, that of the mental activity involved in reviewing the experience. The mental activity may cause emotional discomfort [32], and the untangling of emotional discomfort needs careful consideration of the experience that should lead (if one is aware) to constructive action challenging existing relations and patterns. The end result of reflection is less about the resolution of an experience; instead, it is a better understanding of that experience [33].

Less is known about the difficulties, practicalities, and methods of critical reflection, or the challenges teaching the theory and practice of critical reflection at the university level [16], [17]. A barrier is that higher education institutions often center on questions of 'what' (the nature and boundaries of a problem) and 'how' (the methods for solving it), occasionally addressing 'why' (the underlying purpose), but rarely focus on 'who' in reflection, which broadly speaking, is a person's self-awareness, reflective capacity, and relationships with others [14]. While reflection remains underexplored within higher education, there have been studies examining strategies to support reflective teaching and learning in areas other than computing. For example, learning journals have been found to encourage students to be self-directed and determine their own focus for assignments, anchor new learning with their experiences, and solve problems [34], [35].

Many reflective strategies/frameworks have the same underlying theoretical premise on how to support the reflection process from planning, monitoring, and evaluation. In this study, we considered the relevance of several frameworks for our context. For example, the Gibbs [36] model was analyzed because it involves individuals focusing on their thoughts, feelings, and recommendations for future actions during the reflective process. Gibbs' model has six stages where individuals describe: 1) what happened, 2) their thoughts and feelings during and after the experience, 3) their evaluation of the experience, 4) making sense of the experience, 5) what else they could have done in the situation, and finally, 6) an action plan for if the situation arises in future. Gibbs' model has been used in a variety of educational contexts, such as learning diaries and case studies. Similarly, Kolb [37] created a model of the learning process with planning, action, evaluation, and reflection as a series of steps within the cycle of learning.

After analyzing several models, we focused on the Expert Learner Model by Ertmer and Newby [19] which places the learner as strategic, self-regulated, and reflective. The framework identifies two basic components of metacognition: 1) Metacognitive Knowledge and 2) Metacognitive Control (self-regulation) which interact dynamically to facilitate expert learning (Figure 1).

Figure 1
The Expert Learner Model (Ertmer and Newby, 1996).



Ertmer and Newby [19] argue that before starting a learning task, expert learners think through different ways of approaching the task, drawing on past experiences with similar tasks and choosing a method that fits both the task requirements and the availability of their own resources for the best possible outcome. Expert learners also create a plan that outlines how they intend to reach their goals, regularly monitoring their progress, and considering whether they need to modify their plan. As a result, expert learners are constantly adjusting, removing extra unnecessary steps, and/or using alternative strategies when needed. Expert learners also use reflection to translate what they know about learning into deliberate actions while also overseeing their engagement in the learning process. Therefore, reflection serves as the bridge between metacognitive knowledge and metacognitive control (self-regulation), where reflecting on the learning process can change a person's approach in the future and deepen metacognitive understanding [38].

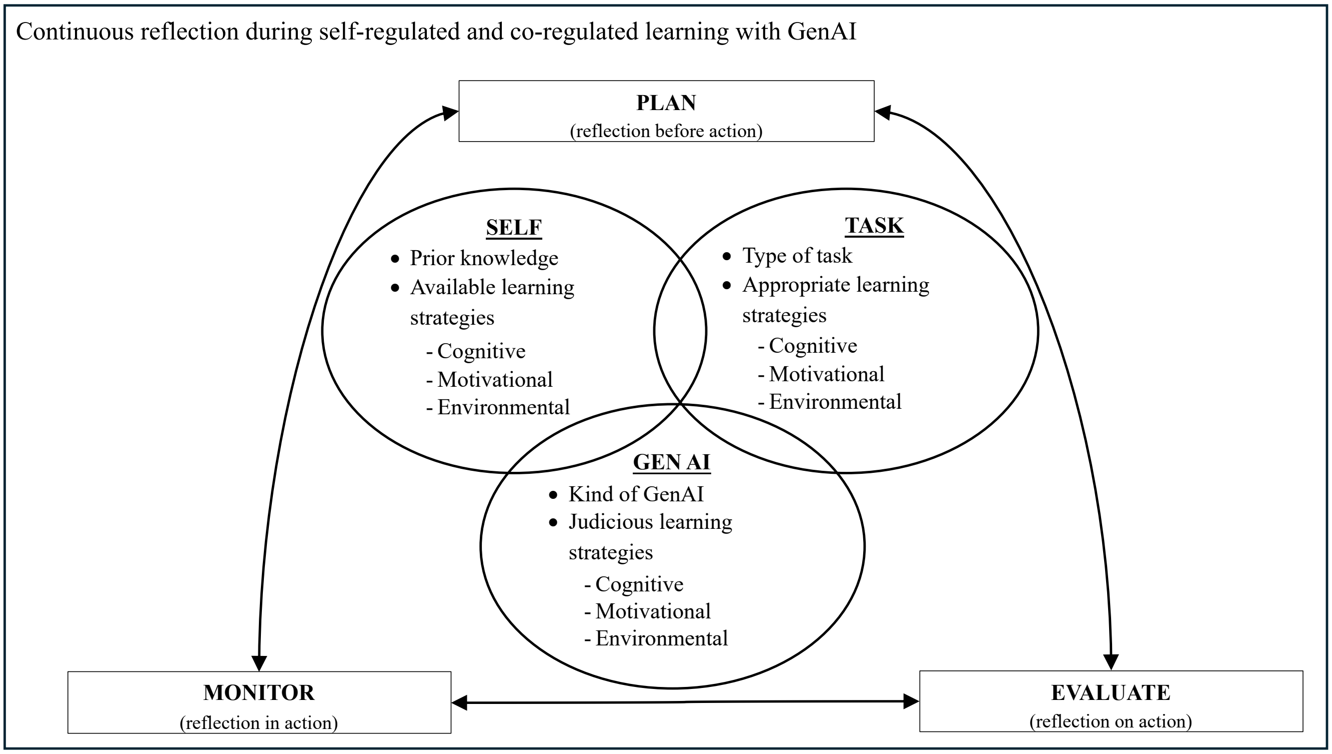
For our proposed framework, extending the expert learner model was relevant because it captures the learning processes necessary to facilitate expert learning. It includes the self, the task and regulation, and has reflection as a core process that facilitates constant awareness and critical improvements. We were interested in how these three core elements (self, task, and regulation) will need to be rethought in the advent of GenAI in the current learning environment and include reflection as a critical process that we need to emphasize and scaffold.

Framework

Our framework (Figure 2) is inspired by Ertmer and Newby's model [19] of the expert learner as strategic, self-regulated, reflective, particularly examining how the learning process has been impacted by the recent upsurge of GenAI in education. We propose a reorganized framework that introduces a co-regulation component with GenAI acting as a learning partner. We also re-represent the Metacognitive Knowledge and Metacognitive Control (self-regulation) components and highlight Reflection as a continuous, catalyzing action that facilitates learning across the three integrated components of Self, Task, and GenAI, as expounded upon below. Overall, we believe the extended framework supports the iterative cycle of planning, monitoring, and evaluating designed to support self- and co-regulated learning between the student, the task requirements, and Generative AI as a learning partner.

Figure 2

Extended GenAI Reflective Framework



1. Knowledge of Self, Task and GenAI

In the original model, Knowledge of Self and Task are represented within the metacognitive knowledge component, which encompasses personal resources (prior knowledge and available learning strategies) and task requirements (type of task, appropriate learning strategies and resources). In our proposed model, we represent them as the Self and Task intersecting components, and we introduce GenAI as a third intersecting component to capture the current learning landscape in the age of AI.

1.1. Knowledge of Self

Consistent with the original model, the Self component represents 'Knowledge of Personal Resources'. This includes a learner's awareness of their prior knowledge and past experiences, as well as their proficiency in employing the various learning strategies required by tasks. These strategies include:

- Cognitive: Processes used to acquire and organize information, such as mnemonics, outlining, and elaboration.
- Motivational: Techniques for maintaining engagement and persistence, including goal setting, self-reinforcement, and positive self-talk.

- Environmental: Management of external factors, such as organizing a study space, scheduling adequate time, and using outside resources.

1.2. Knowledge of Task

Consistent with the original model, the Task component represents 'Knowledge of Task Requirements'. This involves identifying the type of task at hand and specific types of strategies and resources most suited for executing that task. These strategies are:

- Cognitive: Selecting specific comprehension, organizational, or elaboration techniques necessary for the task.
- Motivational: Assessing the amount of effort necessary for task completion and the significance or relevance of the subject matter to the learner.
- Environmental: Determining the optimal study conditions and external resources such as collaboration or consultation required to meet the task objectives.

The components of Knowledge of Self and Task intersect because, for a given task, the learner needs to match their repertoire of abilities (self) to the requirements of the task at hand.

1.3. Knowledge of GenAI

In our proposed model, we introduce GenAI as a third intersecting component alongside Knowledge of Self and Knowledge of Task. To enable expert learning in the AI era, a learner must possess an understanding of GenAI's capabilities, limitations, and implications as a learning partner. This includes identifying:

a) The kind of AI: This involves identifying the specific type of GenAI tool acting as a learning partner. For instance, LLMs such as ChatGPT, Copilot, Gemini, and DeepSeek are designed for broad applications across diverse domains [39]. A learner explores and interacts with these tools' varied interfaces and functionalities, recognizing that each tool possesses unique strengths and limitations for various tasks such as explanation, drafting, brainstorming, and code generation etc. Furthermore, the learner considers the tool's underlying data sources, distinguishing between those drawing from the general internet and those from a specific, trusted institutional library. By understanding these distinctions, the learner can effectively match the GenAI tool's affordances to their own capabilities (self) and the demands of the task.

b) The judicious learning strategies and resources: This involves implementing methods that are effective for collaborating and co-regulating with GenAI tools in relation to the learner's knowledge of Self and Task. This information may be of a:

- **Cognitive Nature**: This involves a technical and strategic understanding of the GenAI tool mechanics. The learner identifies the characteristics of LLM versions, their propensity for hallucinations, and understands their prompting skills impact to ensure quality outputs [40].

- *The Intersection with Self:* The learner needs to critically determine how to employ the GenAI tool as a scaffold to extend their own abilities rather than completely cognitively offloading. This is important as previous work [41] has indicated that the frequent reliance on AI tools is linked to a decline in critical thinking skills due to increased cognitive offloading.
- *The Intersection with Task*: The learner needs to evaluate if, when, and how a specific GenAI tool should be used to meet the specific task requirements. For example, this can require matching task goals with the most effective prompting framework. Unnecessary applications include those where GenAI does not support scientific outcomes or justify the associated risks and costs of cognitive offloading and consequent decline in critical thinking [42].

- **Motivational Nature:** This involves an understanding of the psychological drivers and affective states that sustain the learning process during GenAI collaboration. It means evaluating the tool's potential to support or hinder learning interest, confidence, autonomy, encouragement, enjoyment, attention, self-efficacy, and empowerment among others.
  - *The Intersection with Self:* The learner needs to monitor how the GenAI affects their internal drive. For example, they need to assess if the tool is supporting their self-efficacy. Previous work states that just as important as AI literacy, is AI interest, and positive attitudes in developing AI self-efficacy [43].
  - *The Intersection with Task*: The learner needs to evaluate how GenAI impacts sustained engagement with the learning material to achieve set task goals. For example, assessing task requirements like time constraints, and effort required to ensure that the GenAI is supporting the motivational energy necessary to perform the task.
- **Environmental Nature**: This involves the learner making judicious ethical and contextual considerations as they collaborate with GenAI. It requires an awareness of the rules, risks, and institutional boundaries that govern GenAI usage [18], [44].
  - *The Intersection with Self:* The learner monitors their own role as an ethical agent during the collaboration with GenAI. This involves proactive data privacy considerations, such as evaluating the implications of sharing personal or proprietary information with the tools. The learner maintains academic integrity, transparency, and information literacy, ensuring they adhere to the citation and attribution standards of their specific discipline. Additionally, the learner is knowledgeable about the societal and environmental implications of GenAI tools, such as the impact of their digital footprint [45].
  - *The Intersection with Task*: The learner evaluates the specific task requirements against the GenAI tool's environmental constraints. This includes assessing potential data biases [46] that may skew results of a particular task. The learner

also aligns their GenAI tool of choice and usage with the institutional and instructor-led policies that guide the task.

2. Continuous Self- and Co-regulation through Planning, Monitoring and Evaluating

Consistent with the original Ertmer and Newby framework [19], we used the Plan, Monitor, and Evaluate components to capture the metacognitive control processes of self- and co-regulation that drive successful learning. The authors state that although these three steps are often *"presented in a manner that suggests that each step occurs only once within a single learning activity, in reality they interact and dynamically impact each other in a recursive fashion"* [19, p. 10]. This is why we have represented them in our model as a continuous feedback loop around the metacognitive knowledge components of Self, Task, and GenAI.

The authors further emphasize that expert learners approach tasks with a strategic plan, whether on paper or in mind, which they constantly assess and modify during execution. This dynamic process is why we have highlighted as they did, the specific reflective processes: *Reflection before action* within the Plan component, *Reflection in action* during the Monitor component, and *Reflection on action* through the Evaluate component [15]. It is through this continuous reflection that *"expert learners make constant on-line adjustments, eliminating extraneous steps, implementing alternative strategies, and/or performing unplanned actions whenever necessary"* [19, p. 11].

This perspective is even more relevant now with the introduction of and collaboration with GenAI tools as they may fabricate and hallucinate, such as inventing scholarly citations or presenting plausible sounding but factually incorrect information [47]. Prior research [48], [49] has indicated that GenAI may also lead to students outsourcing their thinking that leads to loss of productive learning struggle, and GenAI can also make it easier for learners to compromise academic integrity. In addition, GenAI can also create echo chambers through algorithmic sycophancy, where the model reflects the learner's own biases or simply agrees with their prompts [48]. Therefore, expert learners must remain active and reflective self- and co-regulators of both their own and with GenAI's learning processes.

2.1. Plan (*Reflection before action*):

Consistent with the original model [19], before beginning a task, expert learners must evaluate four key variables: 1) the task demands, 2) their own personal resources (self), 3) the potential matches between the two, and as introduced in our framework 4) the GenAI tools available. Using Ertmer and Newby's example, if a learner recognizes that notetaking and underlining are effective strategies for identifying the main points of a technical article (Task), and they know they are skilled at underlining but struggle with notetaking (Self), the most effective match is to proceed with underlining. With the introduction of GenAI, the learner must now also consider the implications of using a tool to extract these main points. While GenAI can perform this task much faster, the expert learner reflects on how this choice would affect their engagement with the material and their ability to achieve mastery.

2.2. Monitor (*Reflection in action*):

Monitoring is a complex, real-time process that occurs during the learning act itself. It requires an awareness of one's current actions, an understanding of how those actions fit within the overall learning sequence, and the anticipation of what must be done next [19]. To be effective, learners must remain attentive to feedback regarding the success or failure of their chosen cognitive, motivational, and environmental strategies as they apply to the Self, the Task, and now, the GenAI. This represents real-time self-regulation and co-regulation with GenAI.

While self-regulation has already been established by the Ertmer and Newby, our extended model focuses on adding real-time co-regulation with GenAI. When collaborating with GenAI, the monitoring process becomes a dynamic, iterative cycle: Input through prompting, GenAI processing, and the learner's assessment of the output. This loop requires the expert learner to engage in continuous reflection-in-action across several layers: *1) Reflecting on the Input*: The learner must evaluate their prompting strategy in real-time to ensure they are framing questions effectively and providing context to guide the GenAI. *2) Reflecting on the Output*: Beyond simply confirming if the content appears correct, the learner must verify the accuracy of the information and ensure that ideas are properly attributed or cited to the original authors. *3) Reflecting on Progress*: The learner continuously assesses if they are making progress toward the task goal or if the collaboration has stalled, requiring a change in direction. 4*) Reflecting on Agency:* The learner monitors their own learning state to ensure they are still in control. They decide when the GenAI is providing too much help, leading to passive consumption and reflecting on how to reclaim their learning agency.

2.3. Evaluate (*Reflection on action*)

The final step of the metacognitive control loop is Evaluating through reflection on action, once the task is completed. Consistent with the original model, this stage involves the learner evaluating both the product and the process employed. They judge the quality of the final product and the efficiency of their co-regulation with the GenAI tool.

This post-task reflection is critical for transforming a single interaction into long-term expertise. The learner needs to look back at the co-regulation process to determine whether the GenAI tool served as an effective learning partner. They assess prompting frameworks used in the input, the accuracy of the final output, their affective state and their own level of mastery. By reflecting on the overall learning experience from the task, learners update their Knowledge of Self, Task, and GenAI. This ensures that the insights gained from the current task inform the Planning phase of the next, hence maintaining the iterative and developmental nature of the continuous reflective learning framework.

3. Questions to support the framework

Drawing on the expert learner framework [19], the sample questions in Figure 3 were adapted to explicitly incorporate the use of GenAI as a learning support. The original question prompts learners to plan, monitor, and evaluate their cognitive, motivational, and environmental processes (both task-related and personal), and this served as the foundation for our adaptation. The revised sample questions extend these prompts across all phases of the learning process, ensuring that GenAI use is consistently reflected upon as a tool supporting task completion.

Implications

An implication of our framework adaptation is its potential use as an instructional scaffold to support undergraduate students' development of self- and co-regulated learning when engaging with GenAI. In classroom contexts, the sample questions could be embedded into learning activities, such as structured planning prompts before assignments, guided check-ins during task completion, and post-task reflections, to help students make their use of GenAI intentional and aligned with the learning goals. For example, in an app development course where students can use GenAI to generate ideas and help solve problems, this reflective framework would be helpful for students to develop their thinking around the use of GenAI. Instructors could integrate the framework questions (Appendix A) as students' progress through the task to support the development of metacognitive practices during the GenAI use.

Rather than treating GenAI as a standalone skill or an unregulated tool for their learning, this framework positions GenAI use within established regulatory processes, with the aim of helping students to critically evaluate when, how, and why GenAI supports their learning. Over time, repeated engagement with this reflection framework aims to support learners to internalize the regulatory practices and support the transition toward more expert-like learning behaviors when working with GenAI tools.

Conclusion

This article proposes an extension of the Ertmer and Newby's expert learner framework [19] by incorporating reflection on GenAI tool use as a metacognitive practice. The proposed framework offers a structure to support students to critically evaluate GenAI to plan, monitor, and evaluate their learning to achieve task goals. This means students can be supported to reflect *on* their GenAI usage rather than reflecting solely *with* GenAI, a key difference to other work on reflection and GenAI. Our framework aims to respond to the growing need for approaches that move beyond GenAI technical literacy toward helping students develop self-regulation of their learning in an AI-driven world.

Figure 3

Sample Questions a learner might ask during the three stages of the learning process when using GenAI (adapted from Ertmer & Newby, 1996 and Wang et al., 2025).

Plan(*reflection before action*)

- Cognitive
    - What is the goal of this task, and do I need GenAI to achieve it? (Task)
    - If so, what sections of the task should I perform alone versus with GenAI, and what order of execution will best facilitate my learning? (Task)
    - What do I know about the GenAI tool to support learning about this task? (Self)
- Motivational
    - Does using GenAI require a great deal of concentration and effort? (Task)
    - How do I feel about using a GenAI tool? Do I like using them? (Self)
    - Will my choice to use GenAI for this task keep me engaged and help me manage challenges, or am I offloading the task and the learning to the tool? (Self)
- Environmental
    - Am I aware of any data privacy and academic integrity considerations before I begin using GenAI (Self)
    - What institutional or instructor policies must I follow regarding AI usage? (Task)
    - How might the inherent GenAI model or data biases affect my results for this task? (Task)

Monitor(*reflection in action*)

- Cognitive
    - Are the strategies, like prompting and verification, I have chosen when using GenAI working? Have the task demands changed in any way because I am using GenAI? (Task)
    - Do I understand what I am doing with GenAI? Am I making progress toward the goal? (Self)
- Motivational
    - Is this task holding my attention when using GenAI, and how am I ensuring that I maintain control over my learning instead of passively following the AI? (Task)
    - How am I feeling as I work with GenAI? As I work with GenAI, what is my current confidence level with the material? (Self)
- Environmental
    - What outside materials or resources should be added when I use GenAI for this task? (Task)
    - Am I giving myself the time I need when using GenAI? (Self)
    - Do I notice any biases, echo chambers, or unethical content that could comprise my work? (Task)

Evaluate(*reflection on action*)

- Cognitive
    - How well did my learning approach work when using GenAI? What did I do when strategies didn't work? How could I improve this approach? (Task)
    - When using GenAI, did I achieve my set goals? What did I learn about GenAI? What new goals do I have now when using GenAI for my learning? (Self)
- Motivational
    - How much effort was required to complete this task using GenAI? How did I stay motivated? (Task)
    - How do I feel about the outcome and the process of learning with GenAI? Did I enjoy this work/using it? (Self)
- Environmental
    - Did I encounter any unexpected obstacles when using GenAI? How did I remedy them? (Task)
    - Did I choose the appropriate GenAI tool? Did I choose a good time and place to use it? (Self)
    - Can I identify which parts of the final product are my own thoughts and which were assisted by GenAI for proper attribution? (Self)

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Appendix A

Ertmer & Newby's sample questions a learner might ask during the three stages of the learning process.

Plan

Cognitive

- What is the goal of this lesson/task? (Task)
- What strategies are most effective with this type of task? (Task)
- What do I know about this topic/task? What useful skills do I have? (Personal)

Motivational

- Does this task require a great deal of concentration and effort? (Task)
- How do I feel about this kind of task? Do I like this kind of work? (Personal)

Environmental

- What kind of study conditions are best for meeting the requirements of this task? (Task)
- When and where do I study best? Is that time and place available for this task? (Personal)

Monitor

Cognitive

- Are the strategies I've chosen working with this task? Have the task demands changed in any way? (Task)
- Do I understand what I am doing? Am I making progress toward the goal? (Personal)

Motivational

- Is this task holding my attention? Is this an interesting lesson/topic to me? (Task)
- How am I feeling as I work on this task? What is my level of confidence? (Personal)

Environmental

- How supportive is the learning environment? Do I need to find a new place to work? (Task)
- What outside materials or resources should be added? (Task)
- Am I giving myself the time I need? (Personal)

Evaluate

Cognitive

- How well did my approach work with this task? What did I do when strategies didn't work? (Task)
- When else could I use this approach? How could I improve this approach? (Task)
- Did I achieve the goal? What did I learn about this topic/task? (Personal)
- What new goals do I have now? (Personal)

Motivational

- How much effort was required to complete this task? How did I stay motivated? (Task)
- How do I feel about the outcome? Did I enjoy this work? (Personal)

Environmental

- Did I encounter any unexpected obstacles in completing the task? How did I remedy the problem(s)? (Task)
- How well did I arrange my study environment? Did I choose a good time and place to study? (Personal)