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Beyond Task Completion: A Theoretical Integration and Framework for Guiding Students' ChatGPT Use for Learning

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Abstract

ChatGPT's intuitive interface and instant feedback can either support learning or enable superficial task completion, depending on how it is integrated into academic work. While generative AI has rapidly entered higher education, much existing guidance focuses on policy and academic integrity rather than explaining how AI use interacts with established mechanisms of learning. This conceptual paper contributes to this discussion by developing an explanatory framework for students' ChatGPT use grounded in foundational learning theories. Drawing on cognitive load theory and goal orientation theory and incorporating self-efficacy and task relevance as mediating constructs, the study undertakes a theory-driven synthesis of four perspectives relevant to how students engage with complex academic tasks. The framework brings these perspectives together to clarify how cognitive demands, motivational orientations, perceived competence, and perceived task value may shape students' decisions about when and how to rely on generative AI tools during academic work. The resulting framework illustrates how these mechanisms may influence whether generative AI is used as a scaffold supporting thinking and knowledge construction or as a shortcut that bypasses essential cognitive processes. The article concludes by illustrating how the framework may inform instructional design that aligns AI use with meaningful engagement in disciplinary tasks in higher education.

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Practitioner Notes

1. Students' use of ChatGPT may shift between supporting learning and bypassing cognitive effort depending on task complexity and cognitive load.
2. How generative AI is framed in course design and classroom communication can influence whether students treat it as a learning support or a shortcut.
3. Explicit discussion of AI use may help students recognise when generative tools support their reasoning and when they replace it.
4. Students' confidence in managing complex tasks may influence whether AI tools are used to support learning or to avoid cognitive effort.
5. Framing ChatGPT as a cognitive tool for exploring ideas and refining reasoning may encourage deeper engagement with disciplinary tasks.

Keywords

ChatGPT in higher education, AI-supported learning, framework for guiding AI use

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Introduction

ChatGPT's intuitive interface and instant feedback can either support learning or enable superficial task completion, depending on how it is integrated into academic work. Since its release in November 2022, the tool has rapidly become embedded in higher education, where students commonly use it, or similar interfaces, to generate ideas, summarise texts, support research, and provide personalised tutoring (Dwivedi et al., 2023; von Garrel & Mayer, 2023). While this adoption reflects ChatGPT's intuitive design and versatility, it also introduces significant challenges for learning. Its coherent and authoritative responses may create an illusion of mastery, leading students to overestimate their understanding while bypassing essential cognitive processes such as critical thinking, analysis, and synthesis (Cotton et al., 2024; Walczak & Cellary, 2023). When AI-generated outputs are accepted uncritically, the underlying mental effort required for durable learning may be reduced.

Institutional responses to generative AI in higher education have largely focused on regulation, academic integrity, and ethical use (Sullivan et al., 2023). As a result, guidance for educators often remains reactive or procedural rather than anchored in established learning theory. At the same time, generative AI such as ChatGPT represents more than a policy challenge. As argued by Krammer (2023), these tools constitute a potential epistemic disruption in higher education, creating opportunities for transformation in how knowledge is produced, interpreted, and applied. However, epistemic evolution does not occur automatically. Without a clear understanding of how students engage with AI-supported tasks, there is a risk that such disruption may instead erode essential processes of knowledge construction.

Despite a rapidly expanding body of literature examining opportunities and challenges associated with AI tools such as ChatGPT in education (Kasneci et al., 2023), much of this work has focused on technological capabilities and implementation challenges rather than on integrating generative AI use with established theories of learning. Recent calls for psychologically informed research on education technology (Kizilcec, 2024) underscore the need to examine how cognitive and motivational mechanisms shape AI-supported learning behaviour in real instructional contexts.To address this gap, this article returns to foundational theories of learning and motivation and examines how they can be integrated to account for students' ChatGPT use in higher education and to inform learning-oriented instructional practice.

> **Research question**. How can foundational theories of learning and motivation, specifically cognitive load theory and goal orientation theory, together with the mediating constructs of self-efficacy and task relevance, be integrated to explain students' ChatGPT use in higher education?

To address this question, the article undertakes a theory-driven synthesis of cognitive load theory and goal orientation theory, incorporating self-efficacy and task relevance as interacting constructs. This synthesis results in an explanatory framework for understanding students' AI-supported learning behaviour in higher education. The article then considers the implications of this framework for instructional practice, illustrating how ChatGPT can be positioned as a cognitive tool that supports, rather than replaces, students' engagement with complex academic tasks.

Literature

The following sections presents four theoretical perspectives relevant to understanding students' use of ChatGPT in higher education: (1) cognitive load theory, which explains the cognitive demands associated with learning complex material; (2) goal orientation theory, which explains how students' achievement goals shape their engagement with academic tasks; and the related constructs of (3) self-efficacy and (4) task relevance, which influence students' beliefs about their capabilities and the value they assign to particular learning activities. Together, they provide the theoretical foundation for the framework proposed later in this article. Later examples apply the framework to typical tasks in five disciplines: physics (computations), foreign language and literature (text interpretation), medical studies (case analysis), computer science (programming and algorithm development), and business/management (market analysis).

Cognitive Load Theory

Learning involves acquiring and integrating knowledge, enabling individuals to apply information and skills effectively. Geary (2002, 2008) distinguished between biologically primary knowledge, which humans acquire naturally, and biologically secondary knowledge, which requires structured instruction. Primary knowledge includes abilities such as language, general problem-solving strategies, and social skills acquired through immersion in a suitable environment, without conscious effort or formal instruction. In contrast, acquiring secondary knowledge, such as reading, writing, mathematics, or using complex tools, requires conscious effort and often explicit teaching (Geary, 2008; Sweller, 2023).

Cognitive load theory (CLT) explains how cognitive demands arise and affect learning when students acquire new knowledge (Sweller, 2023; Sweller et al., 2011; Sweller et al., 2019). It emphasises the role of human cognitive architecture in learning—specifically how we process, store, and retrieve information. New information enters working memory, where it is actively processed. Processed information is then encoded into long-term memory, where it is organised into knowledge structures. Unlike working memory, which has severe limitations in both capacity and duration when dealing with novel information, long-term memory has no known limits of capacity or duration. Environmental signals such as words, images, or other sensory inputs activate stored knowledge and enable retrieval from long-term memory. Retrieved knowledge acts as single units, making them easier to handle than multiple new, isolated pieces of information. This retrieval process allows learners to bypass the need to reprocess familiar information, potentially freeing up cognitive resources for new learning (Sweller, 2023).

A central concept in CLT is element interactivity, i.e., the degree to which elements such as symbols, procedures, or concepts that need to be learned, must be processed simultaneously in working memory due to their logical relationships (Chen et al., 2017; Sweller, 2010). For example, solving a two-variable system of equations, such as $x + 4y = 6$ and $2x - 9y = 46$, requires considering each individual symbol and the relationship between them and processing all that information simultaneously in working memory. In contrast, learning a list of vocabulary in a foreign language is a low-element-interactivity task because each word can be learned independently of the others.

Cognitive load refers to the conscious effort required to handle element interactivity. Tasks with many mutually dependent elements place greater demands on working memory than tasks whose elements can be processed in isolation. *Intrinsic cognitive load* is determined by the number of interacting elements relative to learner expertise; what counts as a "single element" for an expert may consist of many interacting elements for a novice. *Extraneous cognitive load* arises from the way information is presented, or tasks are structured. For example, unclear instructions, poorly structured materials, or distracting formats can increase element interactivity without changing what needs to be learned (Sweller, 2010; Chen et al., 2017).

Earlier CLT work treated intrinsic, extraneous, and germane load as three types of cognitive load, with germane load defined as the extra effort devoted to construction of knowledge structures and deep processing (Sweller et al., 1998; Paas et al., 2003). More recent accounts argue that germane load is not a separate category but rather reflects the allocation of working memory resources to processing the interacting elements that constitute intrinsic cognitive load. When extraneous load increases, fewer working memory resources remain available for processing these intrinsic elements (Kalyuga, 2011; Sweller, 2010; Sweller et al., 2011; Sweller et al., 2019). In line with this interpretation, intrinsic and extraneous load are treated as the primary categories of cognitive load, while the term "germane" is used to denote the productive allocation of working memory resources to intrinsic processing.

Successfully process high-element-interactivity material requires learners to manage intrinsic cognitive load by allocating working-memory resources efficiently while minimising extraneous load (Chen et al., 2023; Sweller, 2010). When intrinsic load is high, even modest increases in extraneous load may exceed working memory capacity and impair learning (Chen et al., 2017; Chen et al., 2023; Sweller, 2010). Task complexity is closely linked to element interactivity, with highly complex tasks characterised by multiple interacting elements that must be processed simultaneously (Campbell, 1988; Chen et al., 2023). For complex, high-interactivity tasks, effective instruction therefore aims to reduce extraneous load so that learners can allocate as much of their limited working memory capacity as possible to processing the intrinsic element interactivity that defines the task. Whether students choose to invest this effort, however, is not determined by cognitive conditions alone but also by their motivational orientations toward the task.

Goal Orientation

Goal orientation theory explains how individuals' achievement goals shape their engagement with cognitive tasks. Originating in the work of Dweck (1986), Nicholls (1984), and Ames (1992), the theory integrates personal motivational orientations with contextual influences such as classroom climate and institutional practices. Achievement goals guide how individuals interpret challenges, regulate effort, and respond to success or failure.

Achievement goals are broadly categorised as *mastery goals* and *performance goals* (Ames, 1992; Nicholls, 1984). Mastery goals emphasise competence development and align with a growth mindset, in which ability is viewed as improvable through effort (Dweck, 1986). Mastery-oriented students view challenges as opportunities for growth, using adaptive strategies like persistence, deep learning, and constructive help-seeking. This mindset fosters resilience, intrinsic motivation, and meaningful learning (Kaplan & Maehr, 2007; Utman, 1997).

By contrast, performance goals focus on demonstrating competence relative to others and are traditionally linked to a fixed mindset, where ability is seen as static (Dweck, 1986; Nicholls, 1984).

Early work linked performance goals to maladaptive strategies for managing cognitive demands, such as avoiding challenges that might expose inadequacies, disengaging after failure, refraining from seeking help, and taking shortcuts to complete tasks and look good in front of others (Dweck & Leggett, 1988; Senko & Tropiano, 2016; Urdan & Kaplan, 2020). Subsequent research refined this distinction. Harackiewicz et al. (1998) proposed a multiple-goal perspective in which mastery and certain performance goals can coexist. Elliot and colleagues further distinguished performance-approach goals, which involve striving to demonstrate competence, from performance-avoidance goals, which focus on avoiding failure (Elliot & Harackiewicz, 1996; Elliot & McGregor, 2001; Elliot & Thrash, 2001). Performance-approach goals are often linked to persistence, whereas performance-avoidance goals are associated with anxiety and disengagement (Elliot, 1999; Urdan et al., 2002).

Building on these developments, Hulleman et al. (2010) distinguished *normative performance goals*, which focus on outperforming others, from *appearance performance goals*, which emphasise avoiding perceptions of incompetence. Their meta-analysis showed that normative performance goals predicted positive academic outcomes, whereas appearance performance goals were linked to lower achievement. A later meta-analysis by Senko and Dawson (2017) reinforced these findings, demonstrating that normative performance goals are generally associated with effective learning strategies, while appearance goals are tied to avoidance behaviours such as refraining from seeking help, and self-handicapping (i.e., a deliberate effort to create or emphasise obstacles enabling an external explanation for poor performance).

Goal orientations are shaped by contextual factors including classroom climate, instructional practices, peer norms, and institutional policies. Early academic experiences are particularly formative, as goal orientations are more malleable at this stage (Scherrer et al., 2024). Bardach et al. (2020) found that environments emphasising specific goals encourage students to adopt corresponding personal goals. Mastery-oriented environments tend to promote both personal mastery goals and normative performance goals, fostering academic success and meaningful learning, whereas strongly competitive or high-stakes contexts may heighten avoidance-oriented patterns. Achievement goals are therefore not fixed traits, but dynamic orientations influenced by the learning environment (Fryer & Elliot, 2007). Students' achievement goals, however, do not operate independently of their beliefs about their own capabilities. Whether learners approach challenging tasks with mastery-oriented persistence or adopt more avoidance-oriented strategies is also shaped by their sense of self-efficacy, which influences their willingness to engage with demanding academic work.

Self-Efficacy

Self-efficacy refers to individuals' beliefs about their capability to succeed in specific tasks and is a key determinant of motivation, persistence, and strategic behaviour (Bandura, 1977, 1982, 1986; Schunk & DiBenedetto, 2016). It develops through four primary sources: mastery experiences, vicarious experiences, social persuasion, and interpretations of physiological or emotional states, with authentic prior successes exerting the strongest influence (Bandura, 1986).

Meta-analytic research demonstrates that higher academic self-efficacy is associated with greater persistence, effortful study, and deeper cognitive processing strategies (Phan, 2009; Honicke & Broadbent, 2016). Self-efficacy also interacts with achievement goals, as students who perceive themselves as capable are more likely to adopt adaptive goal orientations and persist in challenging tasks.

Importantly, self-efficacy is malleable and responsive to contextual influences, including instructional design and feedback practices (Schunk & DiBenedetto, 2016). Learning environments that provide structured opportunities for success and emphasise the role of effort and strategy in achievement can strengthen students' efficacy beliefs and promote sustained engagement with cognitively demanding material. However, believing that one can succeed does not necessarily ensure that effort will be invested. Students' willingness to engage with demanding tasks is also shaped by how relevant they perceive those tasks to be for their learning goals.

Task Relevance

Task relevance refers to how students evaluate a task's importance in relation to their academic goals and the effort they are willing to invest. It can be conceptualised along a continuum from peripheral to core, where highly relevant tasks directly support essential learning objectives, while peripheral tasks serve a supplementary function. Importantly, what is considered core or peripheral may shift as students progress through a programme of study. For example, in an introductory physics course, solving simple equations may constitute a core task for developing foundational problem-solving skills. As students advance, such exercises may become peripheral, supporting engagement with more complex modelling tasks. This dynamic quality highlights task relevance as a factor that influences how students allocate cognitive resources and interpret academic demands.

Task relevance interacts with goal orientation and cognitive load management by shaping how students approach effortful tasks. Students who perceive a task as central to their development are more likely to engage deeply with its conceptual demands, whereas tasks perceived as peripheral may invite more strategic or efficiency-oriented engagement. Research on task value indicates that when students construe a task as meaningful and connected to future outcomes, they are more likely to engage more deeply with the task (Harackiewicz & Hulleman, 2010). Task relevance is therefore not inherent in the task itself but constructed through students' interpretations of its purpose and value within a broader academic trajectory. Understanding how such interpretations interact with cognitive demands, motivational orientations, and efficacy beliefs provides the basis for integrating these perspectives into a unified explanatory framework.

Method

The framework presented in this article was developed through a theory-driven synthesis prompted by recurring instructional challenges observed in the author's teaching between 2023 and 2024. During this period, increasing numbers of students appeared to rely on ChatGPT to outsource core elements of reading, analysis, and writing tasks rather than using it to support their own reasoning. These observations motivated an exploration of theoretical perspectives capable of explaining when AI use supports learning and when it undermines it.

The selection of theoretical perspectives was guided by two criteria: (1) their established explanatory power in research on learning and motivation, and (2) their direct relevance to the cognitive and motivational mechanisms implicated in AI-supported academic work. Cognitive load theory accounts for how task complexity and instructional design shape working memory demands (Sweller, 2010; Sweller et al., 2019). Goal orientation theory explains how students' achievement goals influence effort, strategy use, and responses to challenge (Ames, 1992; Hulleman et al., 2010). Self-efficacy theory addresses students' beliefs about their capacity to succeed in demanding tasks (Bandura, 1986). Task relevance captures how students' perceptions of task value influence cognitive investment and goal adoption (Harackiewicz & Hulleman, 2010). Together, these perspectives provide complementary explanatory mechanisms for understanding students' AI-supported learning behaviour.

The integration process was iterative. Key theoretical works within each perspective were reviewed, and their core constructs were mapped against recurring instructional situations observed in classroom AI use. Relationships between constructs were refined through repeated comparison of theoretical propositions and instructional scenarios, with the aim of developing a coherent explanatory model capable of accounting for both scaffold-oriented and shortcut-oriented AI use. The resulting framework therefore reflects conceptual integration rather than a systematic review or meta-analysis. The illustrative strategies and examples presented in the Discussion section were author-developed and informed by prior teaching experience across disciplines, informal piloting of AI-related guidance in classroom settings, and examination of typical curricular tasks in higher education. These examples are intended as conceptual operationalisations of the framework's constructs rather than as empirically validated interventions.

The primary contribution of this study is theoretical clarification and integration. Although classroom experiences informed the identification of the practice problem and the plausibility of the model, the framework itself has not been subjected to systematic empirical testing. Future research is therefore needed to examine how instructional designs derived from the model influence students' cognitive engagement, goal orientations, and patterns of AI use.

Bringing it Together: A Framework for Guiding Students' AI use

The framework, illustrated in Figure 1 integrates four key factors (cognitive load management, goal orientation, self-efficacy, and task relevance) into an explanatory model of students' ChatGPT use in higher education. Rather than treating generative AI as inherently beneficial or harmful, the framework positions its educational effects as contingent upon cognitive and motivational conditions shaped within instructional contexts.

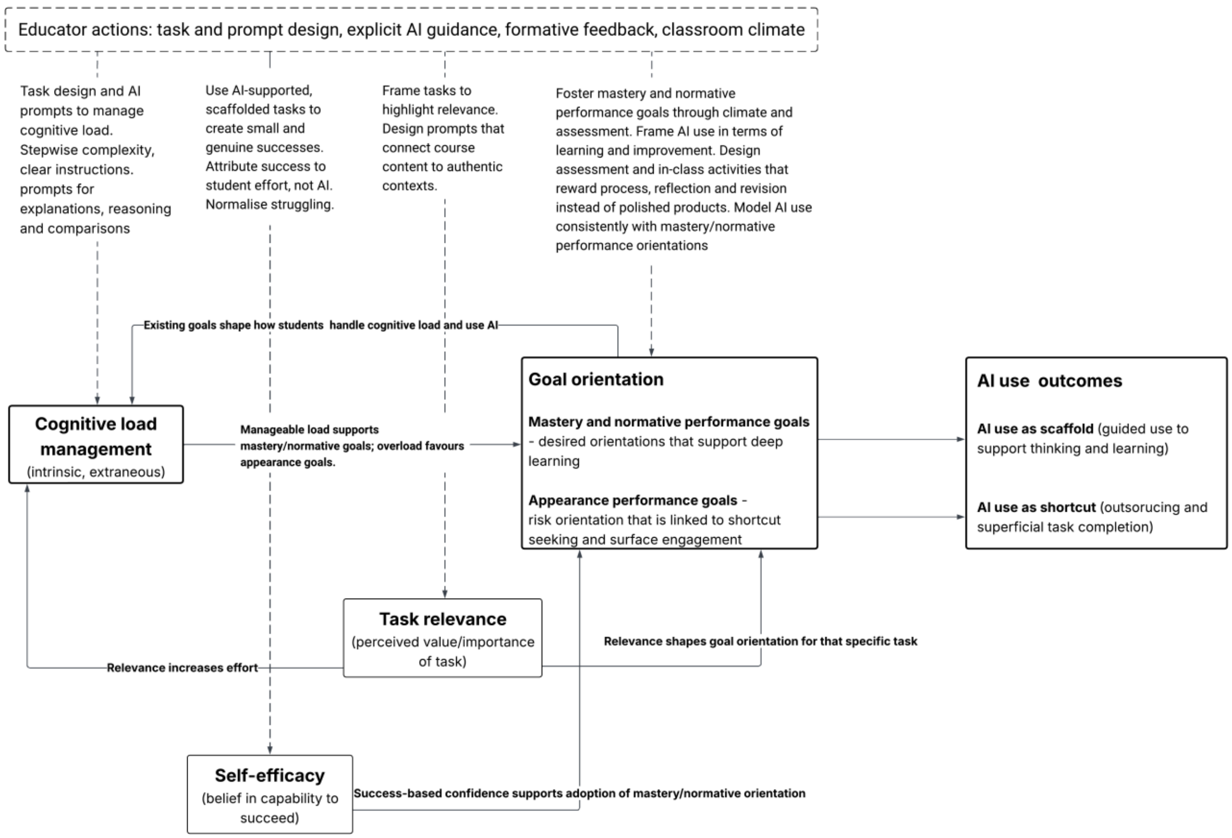
At the cognitive level, the model draws on cognitive load theory to distinguish between intrinsic task complexity and extraneous processing demands. ChatGPT may reduce extraneous load by structuring information, clarifying requirements, or activating prior knowledge. However, when outputs from generative tools such as ChatGPT replace engagement with interacting elements, intrinsic load is bypassed rather than managed. The cognitive function of AI use therefore depends on whether it preserves or bypasses engagement with task complexity.

At the motivational level, the framework incorporates goal orientation theory to explain how students' achievement goals shape their AI use strategies. Mastery and normative performance orientations are associated with persistence and adaptive strategy use (Harackiewicz et al., 1998; Senko & Dawson, 2017), making it more likely that generative tools are used to elaborate, refine, or extend understanding. In contrast, appearance performance goals, linked to avoidance and self-protective behaviours (Hulleman et al., 2010), increase the likelihood that AI is used to minimise effort and protect perceived competence.

Self-efficacy functions as a mediating mechanism within this structure. Students who believe they can succeed in demanding tasks are more likely to sustain engagement and adopt mastery-oriented strategies (Bandura, 1986; Honicke & Broadbent, 2016). When students attribute success primarily to external tools rather than to their own effort and strategies, growth in self-efficacy may be constrained, reinforcing shortcut-oriented patterns of engagement.

Figure 1

Framework explaining scaffold and shortcut patterns of ChatGPT use in higher education



Existing goal orientations guide how students handle cognitive load and how they use AI. When cognitive load is manageable, it tends to support mastery and normative performance goals, whereas overload is more likely to favour appearance-oriented goals. Task relevance influences the effort students are willing to invest and the goals they adopt for specific tasks. Together, these constructs channel students toward using ChatGPT either as a scaffold that supports thinking and learning or as a shortcut characterised by outsourcing and superficial task completion.

Task relevance further shapes how cognitive and motivational mechanisms interact. When tasks are perceived as central to academic or professional development, students may be more willing to tolerate intrinsic cognitive load and engage deeply with complex material (Harackiewicz & Hulleman, 2010). When tasks are construed as peripheral, efficiency considerations may dominate, increasing the likelihood that AI is used to reduce effort rather than support learning.

Discussion

This article addressed the research question of how cognitive load theory and goal orientation theory, supplemented by self-efficacy and task relevance, can be integrated to explain students' ChatGPT use in higher education. The resulting framework positions AI-supported learning not as inherently beneficial or detrimental, but as contingent upon cognitive and motivational conditions shaped within instructional contexts. By bringing together mechanisms from theories of learning and motivation, the model offers a theoretically grounded account of why ChatGPT may function as a scaffold supporting cognitive engagement in some situations, while becoming a shortcut that bypasses essential learning processes in others.

Recent scholarship has called for greater conceptual clarity and practical guidance regarding generative AI in academic settings (Enang & Christopoulou, 2025), alongside broader appeals for a re-examination of educators' roles and competencies in the AI era (UNESCO, 2024). At the same time, research indicates that students frequently use generative AI primarily for task completion rather than for deeper exploration or conceptual understanding (Sallai et al., 2024). Rather than attributing such patterns solely to the affordances of the technology, the present framework suggests that students' AI use may reflect the interaction between cognitive load, prevailing achievement goals, perceived task relevance, and self-efficacy beliefs.

While many students hold a mix of mastery, normative performance, and appearance performance goals, the framework suggests that these orientations do not operate in isolation. In contexts where cognitive load is high, task relevance is unclear, or self-efficacy is fragile, students may be more inclined to rely on generative AI as a means of reducing effort or protecting perceived competence. The accessibility and fluency of ChatGPT may therefore amplify shortcut-oriented tendencies among students with stronger appearance-focused goals.

At the same time, the model identifies points within instructional design where such patterns may be influenced. Because cognitive load, goal orientation, self-efficacy, and task relevance are shaped by classroom structures and discourse (Bardach et al., 2020), educator actions can function as levers within the system. In particular, the framework highlights four areas of influence: structuring tasks and prompts to manage cognitive load, designing scaffolded AI-supported activities that build authentic mastery experiences, framing tasks in ways that emphasise their academic and professional relevance, and fostering mastery and adaptive normative performance orientations through assessment practices and classroom climate.

Practical Implications

The following subsections translate the framework into illustrative instructional designs. These examples demonstrate how cognitive load management, goal orientation, self-efficacy, and task relevance may be operationalised in AI-mediated learning contexts. They are intended as conceptual demonstrations rather than prescriptive models and are offered as theoretically grounded starting points for further empirical examination.

Within the framework, cognitive load management represents a key mechanism through which AI-supported learning becomes either scaffolded or shortcut-oriented. From a cognitive load perspective, instructional design seeks to reduce extraneous load while preserving engagement with intrinsic element interactivity that constitutes task complexity (Chen et al., 2017; Sweller et al., 2019).

Table 1

Illustrative Examples of AI-Supported Cognitive Load Management Across Disciplines

Academic discipline **Task**	**Relatively low complexity** **ChatGPT use**	**Relatively high complexity** **ChatGPT use**
Physics Computations	Solving basic equations like Newton's laws Use ChatGPT as a calculator to verify computations	Designing thermodynamic systems for real-world applications Use ChatGPT to break down calculations into familiar steps and explain underlying principles
Foreign language and literature Text interpretation	Building vocabulary by identifying and translating unfamiliar words Use ChatGPT to clarify word usage and idiomatic expressions	Analysing themes and styles in historical literary works Use ChatGPT to provide context and suggest analytical frameworks
Medical studies Case analysis	Memorising diagnostic criteria for common, single-issue cases Use ChatGPT to generate quizzes or flashcards for self-testing	Diagnosing complex patient cases involving multiple, interacting conditions Use ChatGPT to activate prior knowledge by summarising diagnostic criteria for single-issue cases, summarise recent research on conditions, synthesise patient histories and suggest diagnostic pathways
Computer science Programming and algorithm development	Learning syntax and basic structures of a programming language Use ChatGPT to generate syntax examples, brief code snippets and debugging tips	Optimising algorithms for efficiency and scalability Use ChatGPT to suggest pseudocode and improve performance metrics while providing explanations of syntax and structure to activate relevant knowledge
Business/Management Market analysis	Learning basic business concepts like SWOT analysis Use ChatGPT to explain concepts and create summaries of business frameworks	Developing a market strategy for a specific industry Use ChatGPT to summarise basic business concepts to activate prior knowledge, and refine analysis and structure reports tailored to industry needs

Applied to AI-mediated contexts, the framework suggests that generative tools should be integrated in ways that support engagement with interacting elements rather than displace them. Sequencing tasks with gradually increasing element interactivity allows intrinsic load to remain aligned with learner expertise (Sweller, 2010). Structured AI prompts can further reduce unnecessary search processes and ambiguity, thereby lowering extraneous load while directing attention toward intermediate reasoning processes such as outlining solution steps, clarifying conceptual relationships, or comparing alternative methods.

When students are required to evaluate and apply AI-generated suggestions, working memory resources remain allocated to intrinsic processing. This aligns with accounts that treat “germane” processing as the allocation of working-memory resources to intrinsic element interactivity (Kalyuga, 2011; Sweller et al., 2019). In contrast, when AI-generated outputs substitute for engagement with interacting elements, intrinsic load is effectively bypassed rather than managed. The framework thus clarifies that the critical issue is not AI use per se, but whether its integration sustains cognitive engagement with disciplinary reasoning. Table 1 provides operationalisations of these principles across disciplinary contexts, demonstrating how AI-supported instructional design may manage task complexity without displacing the cognitive effort required for learning.

The framework proposes that mastery and normative performance orientations are more likely to support AI use as a tool for elaboration, refinement, and strategic improvement, consistent with findings linking these goals to persistence and adaptive strategy use (Harackiewicz et al., 1998; Senko & Dawson, 2017). In contrast, appearance performance goals, associated with avoidance and self-protective behaviours, may increase the likelihood that generative AI is used to minimise effort or protect self-presentation (Hulleman et al., 2010; Urdan & Kaplan, 2020).

Because goal orientations are responsive to contextual cues (Bardach et al., 2020), instructional discourse and assessment structures can influence how students position AI tools in relation to their learning. Environments that emphasise growth, competence development, and constructive challenge may increase the likelihood that generative AI is used to support reasoning rather than substitute for engagement. The framework therefore highlights motivational climate as a key lever in shaping AI-supported learning behaviour. Table 2 provides operationalisations of these distinctions across disciplinary contexts. By distinguishing between mastery, normative performance, and appearance performance orientations, the table clarifies why generative AI may support deep engagement in some cases while encouraging surface-level completion in others.

Table 2

Illustrative Examples of AI Use Across Achievement Goal Orientations

Academic discipline ***Task***	**Mastery-oriented AI use**	**Normative performance-oriented AI use (focusing on outperforming others)**	**Appearance performance-oriented AI use (reflecting a focus on demonstrating ability by meeting external expectations)**
Physics *Computations*	Uses ChatGPT to explore underlying principles of equations, test different problem-solving approaches, and develop a deeper conceptual understanding (e.g., applying Newton's laws in real-world scenarios).	Uses ChatGPT to validate computations, optimise efficiency, and refine problem-solving approaches to outperform peers in assessments.	Uses ChatGPT to obtain quick, accurate solutions without engaging in the problem-solving process, prioritising task completion over understanding.
Foreign language and literature *Text interpretation*	Uses ChatGPT to explore cultural nuances, historical context, and rhetorical techniques, engaging in deeper textual analysis.	Uses ChatGPT to refine interpretations and develop unique, sophisticated analyses that stand out in coursework or competitive settings.	Uses ChatGPT to generate full-length essay responses or literary interpretations with minimal personal input, focusing on producing polished assignments without deep engagement.
Medical studies *Case analysis*	Uses ChatGPT to simulate patient interactions, analyse complex cases, and explore differential diagnoses, fostering deeper clinical reasoning.	Uses ChatGPT to refine and structure detailed case responses that stand out in group discussions or competitive evaluations.	Uses ChatGPT to generate pre-formulated diagnostic summaries or treatment plans, prioritising efficiency and correctness over genuine analytical engagement.
Computer science *Programming and algorithm development*	Uses ChatGPT to understand programming paradigms, test algorithms, and troubleshoot inefficiencies through iterative exploration.	Uses ChatGPT to refine algorithms, optimise performance, and create innovative solutions to demonstrate advanced coding skills in competitive environments.	Uses ChatGPT to generate entire code snippets or complete assignments with minimal debugging or understanding, prioritising quick submission over skill development.
Business/ Management *Market analysis*	Uses ChatGPT to explore multiple strategic approaches, analyse real-world case studies, and critically assess business implications for long-term decision-making.	Uses ChatGPT to refine market analyses and develop high-quality reports that surpass peers in depth, insight, and strategic complexity.	Uses ChatGPT to generate polished, well-structured summaries or presentations with little critical evaluation, focusing on meeting assignment expectations efficiently.

Within the framework, self-efficacy functions as a mediating mechanism linking cognitive demands and motivational orientations. Research on self-efficacy indicates that students' beliefs about their capability to succeed shape persistence, strategy use, and willingness to engage with challenging tasks (Bandura, 1986; Schunk & DiBenedetto, 2016). Because mastery experiences are the most influential source of efficacy development, instructional design influences how students interpret success and difficulty.

Applied to AI-mediated contexts, the framework suggests that generative tools should be integrated in ways that preserve students' sense of agency in completing complex tasks. Structuring activities into incremental steps allows students to experience manageable successes while retaining responsibility for core reasoning processes. When AI is positioned as a resource for clarifying intermediate steps or providing feedback rather than producing final outputs, students can attribute progress to their own strategies and effort.

Table 3

Illustrative Examples of Educator-Guided AI Use to Support Self-Efficacy Across Disciplines

Academic discipline ***Task***	**Educator Strategy to Build Self-Efficacy**	**Resulting Student Outcome**
Physics *Computations*	Guide students in using ChatGPT to decompose complex multi-variable equations into smaller, manageable steps while receiving targeted feedback on their approach.	Students develop confidence in breaking down and solving complex equations, increasing persistence when faced with computational challenges.
Foreign language and literature *Text interpretation*	Encourage students to use ChatGPT for historical or cultural context generation, followed by guided critique and synthesis of the information.	Students gain confidence in interpreting texts independently, viewing ChatGPT as a supplementary resource rather than a substitute for critical analysis.
Medical studies *Case analysis*	Model how to use ChatGPT to structure diagnostic pathways, while emphasising the need for clinical reasoning, source evaluation, and professional judgment.	Students develop self-efficacy in synthesising medical information and applying diagnostic reasoning, fostering confidence in complex case analysis.
Computer science *Programming and algorithm development*	Provide structured debugging examples using ChatGPT, gradually shifting responsibility to students as they gain proficiency.	Students build confidence in debugging and optimising algorithms independently, becoming more engaged with advanced programming tasks.
Business/ Management *Market analysis*	Guide students in brainstorming ideas with ChatGPT, requiring them to critically evaluate, refine, and justify AI-generated suggestions.	Students develop self-efficacy in strategic analysis and decision-making, using ChatGPT as a creative tool without over-reliance.

Meta-analytic findings linking self-efficacy to persistence and deep processing (Honicke & Broadbent, 2016; Phan, 2009) support the view that bounded support may strengthen confidence and promote adaptive engagement. The framework therefore highlights the importance of preserving student ownership of evaluation, synthesis, and decision-making in AI-supported tasks. Table 3 provides operationalisations of these principles across disciplinary contexts, showing how educator-guided AI use may foster confidence and persistence without displacing disciplinary reasoning.

Because perceptions of relevance are shaped by instructional framing and programme structure, how tasks are positioned within a course may indirectly influence patterns of AI-supported engagement. The framework therefore suggests that clarifying the purpose and long-term value of tasks may alter how students integrate generative tools into their learning strategies. Table 4 provides operationalisations of how task relevance may shift across stages of disciplinary progression.

Table 4

Illustrative Examples of Shifting Task Relevance Across Disciplines

Academic discipline ***Task***	**Early core task that becomes peripheral as studies progress to more advanced levels**	**Later core task**
Physics *Computations*	Solving basic equations to practise foundational problem-solving.	Modelling complex systems with multi-variable interactions requiring advanced computational methods.
Foreign language and literature *Text interpretation*	Building vocabulary and grammar skills.	Interpreting literary texts within cultural and historical contexts, analysing themes and styles.
Medical studies *Case analysis*	Memorising and reviewing diagnostic criteria for single-condition cases.	Analysing complex patient cases involving multiple interacting conditions, synthesising clinical data.
Computer science *Programming and algorithm development*	Learning and practicing syntax and logic of a programming language.	Developing optimised algorithms, integrating advanced data structures for scalable systems.
Business/Management *Market analysis*	Understanding and summarising foundational business concepts and theories.	Designing strategic business plans, analysing real-world case studies, and applying theoretical frameworks.

Within the framework, task relevance operates as a mediating construct linking cognitive load and goal orientation. Students' willingness to invest effort depends not only on task complexity but also on whether the task is perceived as central to academic or professional development. Research on task value suggests that when activities are construed as meaningful and connected to future outcomes, students are more likely to engage more deeply with the task and persist despite difficulty (Harackiewicz & Hulleman, 2010).

Applied to AI-mediated contexts, the framework proposes that perceptions of relevance influence how generative tools are positioned within learning activities. When a task is perceived as central, students may be more willing to tolerate intrinsic cognitive load and use AI to elaborate or extend understanding. When a task is perceived as peripheral, efficiency considerations may become more salient, increasing the likelihood that AI is used to minimise effort.

Theoretical Implications

The framework illustrates how principles from cognitive load theory may inform interpretations of AI-mediated learning contexts. Rather than treating generative AI as a neutral productivity tool, the model conceptualises ChatGPT as an instructional variable that may influence how learners allocate cognitive resources when working with complex tasks. When AI outputs replace engagement with interacting elements, intrinsic cognitive load may be bypassed rather than managed by the learner. From this perspective, the framework suggests that the educational role of generative AI depends on whether its use preserves or reduces learners' engagement with task complexity. This perspective aligns with broader arguments that generative AI may create opportunities for educators to build more supportive learning environments when integrated deliberately into teaching practice (Eager & Brunton, 2023).

The framework also applies insights from goal orientation research to the context of AI-supported learning. Prior work indicates that mastery and normative performance goals are associated with persistence and adaptive strategy use, whereas appearance performance goals are more closely associated with avoidance and self-protective behaviour (Hulleman et al., 2010; Senko & Dawson, 2017). Interpreting AI use through this lens suggests that students' achievement goals may shape whether generative tools are used to elaborate and refine understanding or primarily to complete tasks efficiently. In this way, the framework highlights how motivational orientations may influence how students position AI tools within their learning strategies.

More broadly, the framework illustrates how cognitive and motivational mechanisms may interact in AI-mediated environments. By positioning self-efficacy and task relevance as mediating constructs, the model suggests that students' engagement with generative tools cannot be understood solely in terms of cognitive demands or motivational orientation. Instead, patterns of AI use may emerge through the interaction between task complexity, perceived competence, and the value students attach to academic tasks. This perspective offers a structured way of interpreting variation in how students incorporate generative AI into their learning activities.

Finally, the framework offers a learning-theoretical perspective that may inform ongoing discussions of AI literacy in higher education (see for example Hazari, 2024; Magrill & Magrill, 2024; Mah & Groß, 2024; Zhou & Schofield, 2024). Rather than focusing primarily on technical proficiency or ethical awareness, this perspective emphasises educators' capacity to design learning conditions that manage cognitive load, support adaptive motivational orientations, strengthen students' sense of competence, and frame tasks as academically meaningful. In this sense, AI literacy can be understood as an extension of pedagogical knowledge grounded in established theories of learning and motivation.

Conclusion

This article addressed the research question of how cognitive load theory and goal orientation theory, supplemented by self-efficacy and task relevance, can be integrated to explain students' ChatGPT use in higher education. The resulting framework offers a theoretically informed lens for understanding why generative AI may function either as a scaffold that supports engagement with complex academic tasks or as a shortcut that enables students to bypass essential learning processes. By integrating cognitive and motivational perspectives, the model highlights how patterns of AI use may be shaped by the interaction between task complexity, achievement goals, perceived competence, and students' interpretations of task value.

The framework is intended as a conceptual guide for interpreting and designing AI-supported learning environments rather than as an empirically validated intervention. While informed by classroom experience, the proposed relationships between constructs require systematic empirical investigation in future research. In particular, further work is needed to examine how instructional design, assessment practices, and classroom climate influence whether generative AI is integrated as a scaffold for learning or used primarily for task completion.

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