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Self-efficacy and instructor support as determinants of ChatGPT effectiveness in student learning

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Abstract

The rapid integration of generative artificial intelligence (AI) tools, such as ChatGPT, is reshaping learning experiences in higher education. However, the psychological and instructional conditions under which these tools enhance academic success remain insufficiently understood, particularly in low resource contexts. Using survey data from 286 university students in Somalia, this study investigates how ChatGPT usage influences students' academic performance and learning outcomes, with particular attention to the mediating roles of academic self-efficacy and cognitive engagement (mental effort), and the moderating role of instructor support. Drawing on the Technology Acceptance Model, Social Cognitive Theory, and Cognitive Load Theory, eight hypotheses were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that ChatGPT usage significantly enhances learning outcomes, self-efficacy, and cognitive engagement; however, its direct effect on academic performance is not statistically significant, suggesting that performance gains do not occur automatically from AI use. Mediation analysis reveals that self-efficacy significantly mediates the relationship between ChatGPT usage and academic performance, whereas cognitive engagement does not. Furthermore, instructor support significantly moderates the relationship between cognitive engagement and academic performance, strengthening the translation of mental effort into achievement. Overall, the findings highlight the critical role of psychological empowerment and instructional support in unlocking the educational benefits of generative AI, particularly in resource constrained higher education contexts.

Keywords Generative AI, Academic performance, Technology acceptance model, Cognitive load theory, Social cognitive theory, Instructor support, Self-efficacy

1 Introduction

The rapid diffusion of generative artificial intelligence (GenAI), particularly large language models such as OpenAI's ChatGPT, is transforming teaching and learning practices in higher education. Unlike earlier educational technologies, ChatGPT enables interactive dialogue, adaptive explanations, and immediate feedback, positioning it as

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a powerful learning companion, rather than a passive information repository [22, 43]. Empirical studies have increasingly reported positive associations between ChatGPT use and student engagement, learning satisfaction, and perceived academic support [14]. Simultaneously, concerns persist regarding overreliance, shallow learning, academic integrity, and the cognitive consequences of delegating learning tasks to AI systems [6]. These mixed findings suggest that the educational value of ChatGPT is not inherent to the technology itself, but depends on how it interacts with learners' psychological processes and instructional contexts.

However, the real-world problem confronting higher education institutions is not merely whether ChatGPT is useful but under what conditions its adoption translates into meaningful and sustainable learning outcomes. Technology adoption in higher education has long been examined in relation to enterprise systems such as Enterprise Resource Planning (ERP), where studies have highlighted organizational readiness, user acceptance, and strategic alignment as critical determinants of success [34]. Recent studies also explore AI-powered tools adoption among university students using innovative methodological approaches [48], highlighting the need to investigate the unique socio-technical dynamics presented by Generative AI. However, Generative AI introduces fundamentally different socio-technical dynamics. Unlike ERP systems, which primarily support administrative integration and institutional efficiency, ChatGPT operates at the cognitive interface between the learner and knowledge construction. It directly shapes students' thinking processes, problem-solving strategies, and academic behavior in real time. This shift from administrative adoption to cognitive augmentation requires moving beyond adoption-focused explanations toward models that account for psychological and instructional mechanisms.

Although empirical studies on ChatGPT in education are expanding rapidly, most treat AI usage as a uniform predictor of outcomes such as engagement, satisfaction, or performance. Meta-analytic evidence shows substantial variability in these effects [14], indicating that ChatGPT does not consistently improve academic performance across contexts. This inconsistency reveals a deeper theoretical gap: existing research rarely explains why *and* through which mechanisms AI use translates or fails to translate into improved academic performance.

Two mechanisms appear particularly important yet insufficiently integrated in prior work. First, cognitive engagement and mental effort core constructs in Cognitive Load Theory [50] capture how learners allocate and regulate cognitive resources when interacting with AI. Second, academic self-efficacy, grounded in Social Cognitive Theory [8], shapes students' motivation, persistence, and strategic learning behaviors. While each construct has been examined independently in educational research, their simultaneous and parallel mediating roles in AI-mediated learning remain underexplored. Moreover, prior studies rarely examine how instructor support conditions these processes, despite growing recognition that AI tools are most effective when embedded in structured pedagogical guidance [23].

These gaps are particularly consequential in low-resource higher education contexts such as Somalia. Universities operate under constraints including limited digital infrastructure, intermittent connectivity, shortages of learning materials, and uneven instructor preparedness. In such environments, ChatGPT often substitutes for textbooks, tutoring services, or learning management systems rather than merely supplementing

them. While this substitution effect may democratize access to information, it also heightens risks of cognitive outsourcing, uncritical reliance, and weak self-regulation [1]. Empirical evidence on how ChatGPT functions within constrained and fragile educational systems remains scarce, limiting the contextual generalizability of AI-in-education theories.

Against this backdrop, this study addresses a focused research problem: how can ChatGPT adoption translate into improved academic performance through identifiable psychological and instructional mechanisms, particularly in low-resource contexts? Rather than examining direct effects alone, this study advances the literature in three ways:

1. It proposes and tests a dual-mediation model in which academic self-efficacy and mental effort operate as parallel and complementary pathways linking ChatGPT usage to academic performance.
2. It integrates the Technology Acceptance Model (TAM), Social Cognitive Theory (SCT), and Cognitive Load Theory (CLT) into a unified explanatory framework, bridging technology adoption, motivational psychology, and cognitive processing in AI-mediated learning.
3. It introduces instructor support as a moderating mechanism, clarifying how pedagogical guidance strengthens or weakens the translation of students' mental effort into performance outcomes.

By shifting the analytical focus from "Does ChatGPT improve performance?" to "Through which psychological and instructional mechanisms does ChatGPT influence performance?", this study offers a more precise explanation for the inconsistent findings reported in prior research.

Accordingly, this study addresses the following research questions:

1. To what extent does ChatGPT usage influence students' academic performance and learning outcomes in higher education?
2. How do academic self-efficacy and mental effort mediate the relationship between ChatGPT usage and academic performance?
3. Does instructor support moderate the relationship between mental effort and academic performance in AI-mediated learning environments.

The study contributes at three levels. Theoretically, it refines AI-in-education scholarship by demonstrating that usage intensity alone is insufficient to explain outcomes; instead, performance effects are shaped by cognitive and motivational mediators operating within instructional contexts. Practically, it offers guidance for designing AI-supported learning environments that enhance self-efficacy, regulate cognitive effort, and prevent unproductive reliance on generative AI. Societally, it contributes evidence from Somalia, helping diversify a literature dominated by well-resourced Global North contexts and informing context-sensitive AI adoption strategies. The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and develops the theoretical framework and hypothesis. Section 3 describes the research design, data collection, and analytical procedures. Section 4 then presents the empirical findings, followed by a Sect. 5 that interprets the results considering theory and prior research. This study concludes with implications, limitations, and directions for future research.

2 Literature review and theoretical framework

2.1 Overview and theoretical positioning

Research on generative artificial intelligence (GenAI), particularly ChatGPT, in higher education has been rapidly growing. However, much of the existing literature remains fragmented, focusing either on adoption intentions, ethical concerns, or short-term performance outcomes, often without coherent theoretical integration. To address this limitation, the present study adopts Social Cognitive Theory (SCT) [7] as the primary explanatory framework, drawing on the Technology Acceptance Model (TAM) [13] and Cognitive Load Theory (CLT) [50] as complementary lenses. This positioning responds directly to recent critiques that AI-in-education research relies too heavily on adoption models without explaining learning mechanisms. SCT provides an overarching logic by explaining how behavior (ChatGPT usage), personal factors (self-efficacy), and environmental conditions (instructor support) interact to shape academic performance. TAM explains why students choose to engage with ChatGPT, and CLT explains how that engagement affects cognitive processing during learning tasks. Figure 1 illustrates this integrated but hierarchically organized framework.

2.2 Impact ChatGPT and student learning

2.2.1 Positive educational outcomes of ChatGPT use

A growing body of empirical research indicates that ChatGPT can enhance student learning when used as an academic support tool, particularly by increasing students' learning motivation, facilitating cognitive engagement, and improving access to academic resources. These effects are especially pronounced in non-Western and resource-constrained contexts, where students often face limited instructional support, overcrowded classrooms and restricted access to learning materials. Studies conducted in Southeast Asia provide empirical support for these benefits. Caratiquit and Caratiquit [64] found that Filipino university students who used ChatGPT as a supplementary learning tool reported higher levels of intrinsic motivation, sustained engagement, and task persistence. The authors attributed these effects to ChatGPT's ability to provide immediate feedback and personalized explanations, which reduced frustration during independent studies. Similarly, Lucas et al. [29] demonstrated that Indonesian students experienced improved conceptual understanding and academic skills, particularly in analytically demanding subjects. Their findings highlight the role of ChatGPT

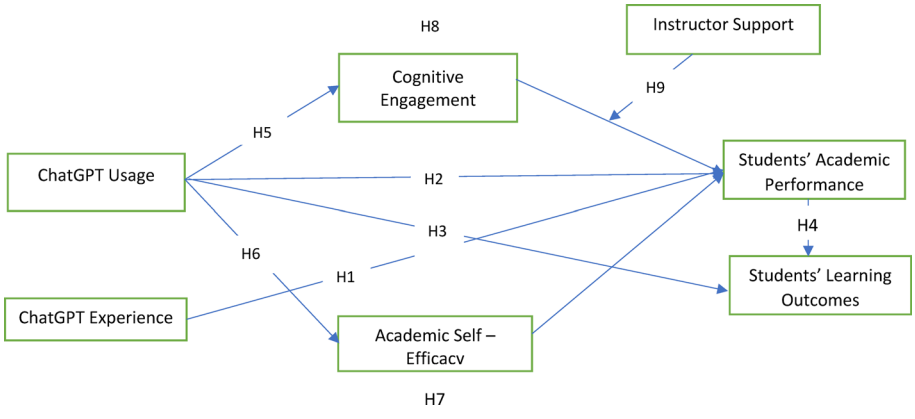


Fig. 1 Research model

in compensating for instructional gaps in under-resourced educational settings. Recent evidence suggests that students' sustained engagement with generative AI is shaped by acceptance-related mechanisms rather than one-time use. For example, Soliman et al. [49] found that the continuous intention to use generative AI significantly predicts perceived learning effectiveness among university students, with perceived usefulness and ease of use acting as critical antecedents.

Beyond motivation and access, several studies have suggested that ChatGPT supports cognitive and metacognitive development. Qiu et al. [37] showed that AI-supported collaborative learning environments encourage students to articulate reasoning, evaluate alternative solutions, and reflect on their understanding, thereby promoting metacognitive awareness. These findings suggest that ChatGPT can function not only as an information provider but also as a cognitive scaffold, supporting deeper engagement when learners actively interact with AI-generated feedback.

In language learning contexts, ChatGPT has additional benefits. Roy and Swargiary [40] found that EFL students who used ChatGPT to draft and revise written assignments exhibited improved writing quality, greater linguistic confidence, and reduced performance anxiety. Importantly, these gains were linked to iterative feedback cycles rather than one-time AI-generated outputs, reinforcing the importance of learner agency in AI-supported learning. Collectively, these studies suggest that ChatGPT's positive educational outcomes are mediated by how students engage with the tool rather than the mere frequency of use. When students use ChatGPT to clarify concepts, test their understanding, and refine their ideas, it can enhance their learning motivation, self-efficacy, and academic performance. These findings provide an empirical basis for examining ChatGPT usage as an antecedent of learning outcomes through psychological and cognitive mechanisms.

2.2.2 Contradictory and negative findings of ChatGPT use

Despite promising evidence, the literature also documents substantial concerns regarding ChatGPT's educational impact, revealing contradictory findings that challenge overly optimistic claims. One of the most widely cited risks is academic dishonesty. Jang [21] reported that a significant proportion of university students used ChatGPT to generate essays and assignments with minimal modification, raising serious concerns about originality and assessment validity. Similarly, Tanvir et al. [52] found a strong association between the use of ChatGPT and plagiarism-related behaviors, particularly in unsupervised learning environments.

Beyond ethical concerns, several studies have highlighted the risks related to cognitive dependency and superficial learning. Azmi et al. [6], using qualitative interviews, found that students expressed anxiety about becoming overly reliant on ChatGPT, perceiving a decline in their independent thinking and analytical skills. These findings align with the concerns raised by Lucas et al. [29], who observed that excessive reliance on AI-generated answers reduced students' willingness to engage in effortful problem-solving, potentially undermining long-term cognitive development.

However, these negative outcomes are not consistent across studies. Liu et al. [28] and Ng et al. [33] demonstrated that ChatGPT can foster deep cognitive engagement when embedded within structured instructional designs that require explanation, reflection, and justification of AI-generated content. In such contexts, students were encouraged

to critically evaluate AI responses rather than accept them uncritically, resulting in improved engagement and reduced anxiety.

This divergence in findings suggests that ChatGPT's educational impact is not inherently positive or negative but is highly contingent on psychological factors (e.g., self-efficacy), cognitive engagement (mental effort), and instructional conditions (instructor support). In the absence of these conditions, ChatGPT risks promoting surface-level learning and dependency. When present, the tool can enhance understanding, confidence, and academic performance.

These contradictions underscore the need for a theoretically grounded model that explains when, how, and under what conditions ChatGPT contributes to meaningful learning, rather than assuming uniform effects across contexts. This unresolved tension in the literature directly motivates the present study's focus on the mediating and moderating mechanisms.

2.2.3 Global vs. Somali context

Most empirical studies on ChatGPT and generative AI in education have been conducted within high-resource, predominantly Western or East Asian higher education systems where AI tools are typically integrated into well-established learning ecosystems. In these contexts, ChatGPT functions as a supplementary learning aid, complementing structured curricula, stable digital infrastructure, learning management systems and consistent instructor support [27, 33]. Students in such environments generally have access to textbooks, academic databases, tutoring services, and institutional guidelines that govern responsible AI use. Consequently, AI adoption tends to enhance existing pedagogical practices rather than compensate for systemic deficiencies.

In contrast, low-resource and fragile higher-education systems, such as those found in Somalia and similar post-conflict contexts, present a markedly different educational landscape. Universities often operate under conditions of limited instructional materials, insufficient library resources, high student–faculty ratios, intermittent Internet connectivity, and minimal access to digital learning platforms. Within this context, ChatGPT is not merely a complementary tool but frequently serves as a substitute for unavailable academic resources, including textbooks, reference materials and individualized academic support. Consequently, students may rely more heavily on AI tools for explanations, examples, and guidance, increasing the cognitive and pedagogical weight of ChatGPT-assisted learning.

This contextual divergence has important theoretical and empirical implications for this study. First, the psychological demands on students in low-resource environments may differ substantially from those in high-resource environments. Greater reliance on AI tools may heighten the role of academic self-efficacy, as students must independently evaluate, interpret, and apply AI-generated information without extensive instructional support. Second, mental effort and cognitive engagement may vary depending on whether ChatGPT is used to support higher-order learning or compensate for foundational instructional gaps. Third, instructor support, even if limited, is a critical moderating factor in guiding ethical use, preventing overreliance, and fostering critical engagement with AI output.

Despite these contextual distinctions, empirical evidence from Somalia and comparable low-income or fragile educational systems remains extremely limited. Most existing

studies implicitly assume stable institutional support and digitally mature environments, constraining the external validity and generalizability of their findings. This imbalance in the literature obscures how AI-supported learning functions under constrained institutional conditions, where technology adoption interacts more strongly with self-regulation, cognitive effort, and instructional guidance.

Accordingly, examining ChatGPT usage in the Somali higher education context provides an important opportunity to extend existing theory beyond Western-centric assumptions. By situating AI-assisted learning within a low-resource environment, this study contributes context-sensitive insights into how generative AI influences academic performance and learning outcomes when institutional support structures are lacking. This study responds directly to calls for more inclusive, globally representative research on educational technologies and offers practical implications for policymakers and educators operating in similar contexts.

2.3 ChatGPT usage, academic performance, and learning outcomes

A growing body of empirical research documents the educational potential of ChatGPT and similar generative AI tools in higher-education settings. Studies conducted across diverse, largely non-Western contexts indicate that ChatGPT can enhance students' learning motivation, productivity, and engagement when deployed as an academic support resource rather than as a replacement for learning activities [46, 64]. In these settings, ChatGPT often serves as an accessible, on-demand learning aid that complements limited instructional resources, thereby supporting independent learning and task completion.

Beyond motivation, research has highlighted ChatGPT's role in supporting higher-order learning processes. Liu et al. [28] demonstrated that ChatGPT can function as a virtual tutor in collaborative learning environments by prompting reflection, supporting metacognitive regulation, and facilitating structured problem-solving. In language learning contexts, particularly English as a Foreign Language (EFL), ChatGPT-assisted feedback has been shown to improve writing quality and reduce learning anxiety by providing timely explanations, examples, and scaffolding [40]. These findings suggest that ChatGPT's educational value lies not only in information provision, but also in its capacity to support learning processes that traditionally require individualized instructor attention.

Simultaneously, the literature reports substantial risks and inconsistencies in learning outcomes. Several studies have documented heightened concerns regarding academic dishonesty, plagiarism, and the uncritical submission of AI-generated content [21, 52]. Qualitative evidence further indicates that excessive reliance on ChatGPT may undermine students' analytical reasoning, critical thinking, and writing development, particularly when AI outputs are accepted without evaluation [6, 29]. Additionally, concerns regarding misinformation, hallucinations, and embedded biases in AI-generated responses highlight the pedagogical risks of unguided AI use [3]. Taken together, these mixed findings suggest that ChatGPT's impact on academic performance is conditional, rather than deterministic. Positive outcomes appear more likely when ChatGPT use is accompanied by adequate cognitive engagement, self-regulation, and instructional guidance, whereas negative outcomes emerge under conditions of overreliance and minimal pedagogical structure. This inconsistency underscores the need to move beyond simple

direct-effect models and examine how and under what conditions ChatGPT use translates into improved learning outcomes.

2.4 Mediating role of cognitive engagement (mental effort)

Cognitive engagement, operationalized in this study through task-relevant mental effort, refers to the extent to which learners actively process, integrate, and apply information during learning activities. From the perspective of Cognitive Load Theory (CLT), learning effectiveness depends not on minimizing mental effort per se, but on optimizing the allocation of cognitive resources across intrinsic, extraneous, and germane cognitive loads [50].

Empirical research indicates that ChatGPT can reduce extraneous cognitive load by simplifying information retrieval, generating explanations, and supporting routine problem solving tasks [5, 56]. Such reductions may free cognitive resources for more meaningful learning, particularly for novice learners and students operating in resource-constrained or second-language learning contexts. However, when ChatGPT is used primarily as a shortcut to answers, it may inadvertently suppress the germane cognitive load, resulting in surface-level engagement and limited knowledge construction [60].

Conversely, when ChatGPT is embedded within learning tasks that require explanation, comparison, justification, or reflection, it can stimulate germane mental effort and deeper cognitive engagement in students. Santhosh et al. [41] demonstratede that AI-supported learning promotes meaningful learning outcomes only when instructional design encourages active cognitive processing rather than passive consumption of AI-generated content. These findings underscore that ChatGPT does not inherently increase or decrease mental effort; rather, its cognitive impact is task dependent and pedagogically mediated.

Accordingly, this study conceptualizes cognitive engagement (mental effort) as a mediating mechanism that explains how ChatGPT usage translates to academic performance. Rather than exerting a uniform or direct effect, ChatGPT influences learning outcomes indirectly by shaping the depth and quality of students' cognitive engagement, which determines whether AI-supported learning leads to meaningful academic improvement.

2.5 Mediating role of academic self-efficacy

Academic self-efficacy, defined as students' beliefs in their capability to successfully perform academic tasks, is a central construct in Social Cognitive Theory and a robust predictor of engagement, persistence, and achievement. In AI-supported learning contexts, self-efficacy plays a critical role in determining whether students use ChatGPT strategically or rely on it. ChatGPT can enhance academic self-efficacy by providing immediate feedback, personalized explanations, and opportunities for successful task completion, thereby reducing anxiety and increasing confidence [32]. Students with higher self-efficacy are more likely to view ChatGPT as a learning aid rather than a substitute for thinking, enabling them to critically evaluate AI outputs and integrate them into their own understanding [2]. Empirical evidence supports the mediating role of self-efficacy in AI-assisted learning. Wang et al. [57] found that self-efficacy mediates the relationship between AI adoption and learning engagement, while Chen et al. [10] showed that higher self-efficacy mitigates over-reliance on generative AI tools. These findings indicate that self-efficacy functions as a psychological pathway through which ChatGPT

influences academic performance. Consistent with Social Cognitive Theory, this study positions academic self-efficacy as a key mediator that explains how students' interactions with ChatGPT translate into learning outcomes, emphasizing agency and self-regulation in AI-mediated education.

2.6 Moderating role of instructor support

Instructor support represents the environmental component of Social Cognitive Theory and remains pivotal in AI-mediated learning environments. At the individual level, instructor support encompasses guidance on appropriate AI use, task design, feedback provision, and establishing ethical and academic norms. Prior research has demonstrated that strong instructor support enhances students' capacity to integrate AI tools responsibly, maintain critical thinking, and develop self-regulated learning behaviors [4, 44]. Instructors play a key role in directing mental effort, ensuring that ChatGPT encourages meaningful cognitive engagement, rather than passive reliance. High levels of instructor support strengthen the relationship between mental effort and academic performance by scaffolding tasks, clarifying expectations, and modeling critical engagement with AI-generated content. Conversely, low instructor support may allow AI to devolve into surface-level task completion, thereby limiting the benefits of cognitive effort.

Beyond these individual-level actions, effective instructor support is embedded in broader institutional and strategic contexts. Research on digital transformation highlights that organizations leveraging new technologies rely on data-driven decision-making, digital leadership, and supportive organizational culture to translate technological adoption into meaningful learning and sustainable advantages [58]. Analogously, universities and faculties must implement institutional strategies, professional development programs, and AI governance policies that provide instructors with the tools, norms, and guidance to use ChatGPT in a pedagogically effective manner. In this view, instructor support is not only a micro-level classroom behavior but also a meso-level environmental factor shaped by institutional digital strategy and leadership practices. This broader conceptualization ensures that students' cognitive engagement and academic self-efficacy are effectively translated into performance gains, particularly in low-resource higher-education contexts. Accordingly, this study conceptualizes instructor support as a moderator that conditions the effectiveness of mental effort in translating ChatGPT's usage into academic success. This positioning aligns with Social Cognitive Theory by emphasizing the interaction between personal, behavioral, and environmental factors, while also situating classroom-level support within a larger institutional digital ecosystem.

2.7 Theoretical background and integration

To enhance conceptual coherence and theoretical transparency, this study adopts Social Cognitive Theory (SCT) as the primary explanatory lens, with the Technology Acceptance Model (TAM) and Cognitive Load Theory (CLT) as supporting perspectives. This layered approach enables a focused explanation of how ChatGPT usage translates into academic outcomes through psychological and cognitive mechanisms while avoiding theoretical redundancy. Each theory is explicitly linked to the hypothesized relationships (H1–H8), ensuring alignment between the theory, model, and empirical testing.

2.7.1 Integrated theoretical foundations

At its core, the model is grounded in Social Cognitive Theory [7], which conceptualizes learning as the reciprocal interaction among behavior, personal beliefs, and environmental influences. Within this triadic structure, ChatGPT usage represents a behavioral factor, academic self-efficacy reflects a personal cognitive belief, and instructor support constitutes an environmental condition. SCT therefore provides the primary explanatory logic for how AI usage translates into academic performance through self-regulatory mechanisms. Academic self-efficacy is central because it determines how students regulate effort, evaluate AI-generated content, and persist in academic tasks. Prior research confirms that self-efficacy mediates relationships between digital tool usage and performance outcomes, while also mitigating over-reliance on AI systems by encouraging independent reasoning [30, 57, 58]. Accordingly, in the present model, self-efficacy functions as a belief-driven mediator linking ChatGPT usage to academic performance.

Cognitive Load Theory [51] complements this perspective by clarifying the cognitive mechanism underlying AI-supported learning. Rather than conceptualizing cognitive load as uniformly beneficial or harmful, this study operationalizes mental effort as an indicator of depth of cognitive processing. While ChatGPT may reduce extraneous load by simplifying explanations, excessive reliance may diminish germane load and weaken meaningful engagement [60]. Thus, mental effort serves as a second mediator, capturing how students cognitively process AI-supported tasks.

The Technology Acceptance Model [13] plays a supportive but bounded role in the framework. Importantly, TAM is not empirically tested as a full structural component in the present study; rather, it functions as a background adoption theory that explains the preconditions for observable usage behavior. TAM posits that perceived usefulness and perceived ease of use shape behavioral intention, which subsequently predicts actual system use. In line with this causal sequence, the study treats sustained ChatGPT usage as a behavioral proxy reflecting prior acceptance and intention-formation processes. This operational decision is theoretically justified because usage behavior in TAM is understood as the ultimate outcome of acceptance beliefs, and modeling usage directly allows the study to focus on post-adoption learning mechanisms rather than re-testing established adoption relationships.

Moreover, the research objective is not to explain why students adopt ChatGPT, but to examine what happens after adoption specifically, how usage interacts with self-efficacy, mental effort, and instructor support to influence academic performance. Including perceived usefulness and ease of use as additional constructs would shift the analytical focus toward adoption determinants rather than learning mechanisms, thereby diluting the study's explanatory emphasis. Therefore, TAM serves as a theoretical foundation that legitimizes ChatGPT usage as a meaningful behavioral antecedent, while the primary explanatory mechanisms linking usage to performance are derived from Social Cognitive Theory and Cognitive Load Theory.

By explicitly positioning TAM as a background theory rather than a tested framework, the model avoids theoretical overextension and maintains conceptual parsimony, ensuring alignment between theoretical scope and empirical objectives. Instructor support is incorporated as an environmental moderator consistent with SCT. By modeling appropriate AI use, structuring reflective tasks, and reinforcing self-regulation strategies, instructors shape how effectively students translate mental effort into academic

performance. This moderation perspective ensures that learning outcomes are not attributed solely to technology usage, but to the interaction between AI engagement and pedagogical context.

2.7.2 Unified explanatory logic

In summary, the integrated framework follows a coherent progression: technology acceptance enables ChatGPT usage (TAM); usage influences belief-based self-regulation (self-efficacy) and cognitive engagement (mental effort) (SCT and CLT); and instructor support conditions whether these mechanisms culminate in improved academic performance (SCT). By assigning each theory a distinct functional role, the model avoids redundancy and clarifies the causal chain underlying AI-mediated learning.

This streamlined integration strengthens theoretical transparency by demonstrating that ChatGPT's educational impact is not deterministic. Rather, its effectiveness emerges from the interplay between behavioral adoption, psychological regulation, cognitive processing, and instructional scaffolding.

2.8 Research gaps

Despite the rapidly growing body of research on ChatGPT and generative AI in higher education, several critical gaps remain that limit both theoretical advancement and practical guidance. First, most existing studies focus on direct relationships between ChatGPT usage and learning outcomes such as engagement, performance, or satisfaction. While these studies establish whether AI tools matter, they provide limited insight into how and why these effects occur. Psychological and cognitive mechanisms central to learning theory are often treated implicitly or omitted altogether. As a result, prior research offers an incomplete explanation of the processes through which ChatGPT use translates into academic outcomes.

Second, although individual mediators such as self-efficacy or cognitive load have been examined in isolation, very few studies simultaneously test multiple mediating mechanisms. In particular, the combined and parallel roles of academic self-efficacy (a motivational psychological mechanism) and mental effort (a cognitive mechanism) remain underexplored. This gap is theoretically significant because learning with AI is inherently both cognitive and self-regulatory, requiring an integrated explanatory model rather than single-path mediation. Third, the moderating role of instructor support has been largely overlooked in empirical AI-in-education research. Existing studies often treat AI use as an individual behavior, neglecting the instructional environment in which it is embedded. This omission is notable given evidence from Social Cognitive Theory and instructional design research that environmental support conditions whether technology use leads to deep learning or surface-level task completion. Consequently, little is known about how instructor guidance shapes the effectiveness of students' cognitive engagement when using ChatGPT. Fourth, the literature reports contradictory empirical findings regarding ChatGPT's educational value. While some studies document enhanced engagement, motivation, and learning quality, others highlight risks related to over-reliance, academic dishonesty, and diminished critical thinking. These inconsistencies are rarely theorized or empirically explained, reinforcing the need for models that account for conditional effects, rather than assuming ChatGPT is uniformly beneficial or harmful. Finally, there is a pronounced contextual gap in the literature. Most empirical

studies have been conducted in high-resource, Western higher education systems, where AI tools supplement robust instructional infrastructures. In contrast, low-resource and non-Western contexts such as Somalia remain largely absent from AI-in-education research. In such settings, ChatGPT may serve as a substitute rather than a supplement for academic support, potentially amplifying both its benefits and risks. The lack of evidence from fragile or resource-constrained systems limits the generalizability of existing findings and obscures the role of instructor support and self-regulation under constrained conditions. By addressing these gaps, the present study contributes to theory by integrating Social Cognitive Theory as a primary lens, supported by TAM and Cognitive Load Theory, to explain not only whether ChatGPT affects learning, but through which psychological and cognitive mechanisms and under what instructional conditions. Practically, the study offers context-sensitive insights to inform responsible and pedagogically grounded AI implementation in low-resource higher education systems.

2.9 Conceptual framework and hypotheses

The proposed conceptual framework explains how ChatGPT usage influences students' academic performance and learning outcomes through psychological and cognitive mechanisms, while accounting for the instructional context. Specifically, academic self-efficacy and mental effort are conceptualized as mediating variables that explain how ChatGPT translates into academic performance, and instructor support is modeled as a moderator that conditions the effectiveness of cognitive engagement. This framework reflects both individual adaptation processes and instructional design influences in AI-supported learning environments.

2.9.1 ChatGPT experience and students' academic performance

Emerging research suggests that the extent of students' experience with ChatGPT or similar generative AI tools significantly influences academic outcomes, above and beyond simple usage frequency. While many studies examine ChatGPT use in general, few explicitly differentiate users by experience level or proficiency. Yet, descriptive evidence indicates that students develop varying levels of strategic competence, prompting skills, and critical evaluation capacity as they interact repeatedly with AI tools (e.g., the ability to formulate high-quality prompts, filter outputs, and revise AI-generated content). These experiential differences shape how effectively students integrate AI into their learning processes and thereby influence academic performance. Empirical studies broadly report positive effects of ChatGPT use on performance when students perceive the tool as useful and easy to use; active utilization has been shown to correlate positively with academic performance and engagement in higher education [68] . Similarly, research examining ChatGPT's impact on creative and academic tasks reports positive associations between AI use and performance outcomes, underscoring the role of sustained interaction with the tool in enhancing task efficiency, clarity of learning, and perceived academic achievement. Beyond generalized use effects, experience appears to differentiate learning outcomes. Studies linking students' perceptions and engagement levels to performance suggest that deeper engagement often characteristic of more experienced users—is associated with stronger academic outcomes [62]. Moreover, exploratory research indicates that students who interact more conceptually with AI (e.g., by posing elaborative prompts and critically evaluating responses) tend to demonstrate

improved task performance. The importance of experience is further supported by research on AI literacy and familiarity, which shows that students with greater competence in AI use are better able to manage cognitive demands and leverage AI to support rather than replace their cognitive processes. Collectively, this body of evidence indicates that accumulated experience with ChatGPT enhances students' ability to translate AI usage into meaningful academic gains.

H1 *ChatGPT experience has a positive effect on students' academic performance.*

2.9.2 ChatGPT usage and academic performance

ChatGPT has emerged as an academic support tool that provides explanations, feedback, and learning assistance. Drawing on the Technology Acceptance Model, students' actual use of ChatGPT reflects prior perceptions of its usefulness and ease of use, which motivate sustained engagement with the tool [13, 49]. Empirical studies show that ChatGPT usage can enhance engagement, task efficiency, and academic performance when used to support learning activities [27, 64]. There``fore, the study proposes the following hypothesis:

H2 *ChatGPT usage has a significant positive effect on students' academic performance.*

H3 *ChatGPT usage has a significant positive effect on students' learning outcome.*

2.9.3 Academic performance and learning outcomes

Academic performance represents students' ability to successfully complete assessments and learning tasks, which subsequently contributes to broader learning outcomes such as knowledge acquisition, skill development, and conceptual understanding. Prior research consistently demonstrates that higher academic performance predicts improved learning outcomes across instructional contexts [65]. Accordingly, the following hypothesis is proposed:

H4 *Academic performance has a significant positive effect on students' learning outcomes.*

2.9.4 ChatGPT usage and cognitive engagement

Cognitive engagement refers to the depth of active cognitive processing that students invest in learning tasks, reflecting germane load rather than mere effort. From a Cognitive Load Theory (CLT) perspective, ChatGPT can reduce extraneous cognitive load by simplifying information retrieval and clarifying explanations, while simultaneously shaping germane cognitive load by influencing how deeply students process and integrate knowledge [50, 60]. When students actively use ChatGPT to compare concepts, reflect on outputs, or solve problems, cognitive engagement is enhanced. In contrast, passive or unstructured reliance on AI-generated content may lead to superficial processing and lower engagement. Accordingly, ChatGPT usage is expected to positively influence students' cognitive engagement, capturing both the quality and depth of learning rather than simply increasing effort. This framing aligns with Social Cognitive Theory, where engagement is mediated by self-efficacy and moderated by instructor support, and provides a more nuanced theoretical justification for H4.

H5 *ChatGPT usage positively influences students' cognitive engagement in learning tasks.*

2.9.5 Mediating role of mental effort

Cognitive engagement represents the extent to which students invest task-relevant, meaningful mental resources in learning activities, reflecting germane cognitive load rather than mere cognitive effort. Prior research grounded in Cognitive Load Theory and learning sciences consistently shows that deeper cognitive engagement such as analyzing, reflecting, and integrating information s associated with superior academic performance and durable learning outcomes [41, 50].

In AI-supported learning environments, ChatGPT does not uniformly increase or decrease cognitive effort. Instead, its educational impact depends on how students engage with the tool. When ChatGPT is used for explanation, comparison, and guided problem-solving, it can stimulate higher levels of cognitive engagement by encouraging active processing and knowledge construction. Conversely, uncritical or passive reliance on AI-generated responses may suppress meaningful engagement and weaken learning outcomes [60].

Accordingly, this study conceptualizes cognitive engagement as a mediating mechanism that explains why ChatGPT usage does not automatically translate into higher academic performance. Rather than exerting a direct effect, ChatGPT influences performance through its capacity to shape the depth and quality of students' cognitive processing, which is further conditioned by instructional context and learner self-regulation.

H6 *Cognitive engagement mediates the relationship between ChatGPT usage and students' academic performance.*

2.9.6 ChatGPT usage and academic self-efficacy

According to Social Cognitive Theory, academic self-efficacy reflects students' beliefs in their ability to successfully perform learning tasks and is a strong predictor of engagement, persistence, and achievement [7]. ChatGPT can enhance self-efficacy by providing immediate feedback, reducing anxiety, and enabling successful task completion [32]. Empirical studies indicate that students who use AI tools effectively report higher confidence in their learning capabilities [33]. Therefore, the following hypothesis is proposed:

H7 *ChatGPT usage has a significant positive effect on students' academic self-efficacy.*

2.9.7 Mediating role of academic self-efficacy

Students with higher academic self-efficacy are more likely to regulate their learning, critically evaluate AI-generated content, and persist in challenging tasks. Prior research confirms that self-efficacy mediates the relationship between technology use and academic performance [10, 56]. Accordingly, academic self-efficacy is expected to serve as a psychological pathway linking ChatGPT usage to academic performance.

H8 *Academic self-efficacy mediates the relationship between ChatGPT usage and students' academic performance.*

2.9.8 Moderating role of instructor support

Instructor support represents the environmental component of Social Cognitive Theory and plays a crucial role in shaping how students engage with AI tools. Through guidance, feedback, and instructional scaffolding, instructors help students use ChatGPT responsibly and maintain critical engagement [4, 44]. High levels of instructor support are expected to strengthen the positive effect of mental effort on academic performance.

H9 *Instructor support moderates the relationship between mental effort and academic performance, such that the relationship is stronger when instructor support is high.*

2.10 Research model

Based on the integrated theoretical foundation discussed in the preceding sections and the identified research gaps, this study proposes an extended conceptual research model examining the impact of ChatGPT usage on students' academic performance and learning outcomes. The model incorporates academic self-efficacy and cognitive engagement (mental effort) as parallel mediators, instructor support as a moderator, and ChatGPT experience as an exogenous control variable (see Fig. 1; Table 1). The model is primarily grounded in Social Cognitive Theory (SCT) [7], complemented by the Technology Acceptance Model (TAM) [13] and Cognitive Load Theory (CLT) [50]. Together, these frameworks explain how technological engagement, psychological beliefs, cognitive processes, and instructional conditions interact to shape learning outcomes in AI-supported educational environments.

SCT provides the central explanatory lens by emphasizing reciprocal interactions between personal factors (academic self-efficacy), behaviors (ChatGPT usage and cognitive engagement), and environmental influences (instructor support). Academic self-efficacy represents a core psychological mechanism through which students regulate their learning, evaluate AI-generated outputs, and persist in challenging tasks. Instructor support functions as an environmental moderator that conditions how effectively cognitive engagement translates into academic performance.

TAM contributes a complementary perspective by framing ChatGPT usage as a behavioral outcome of prior acceptance processes. Although perceived usefulness and perceived ease of use are not explicitly modeled, actual ChatGPT usage is treated as an enacted technology-use behavior that influences academic performance and learning outcomes once adoption has occurred. Sustained and purposeful use reflects internalized perceptions of usefulness, which subsequently affect academic outcomes. Recent empirical evidence supports this assumption, demonstrating that sustained technology use predicts learning effectiveness in digital learning environments [49].

CLT further informs the model by explaining how ChatGPT shapes learning through its influence on cognitive engagement (mental effort). AI tools may reduce extraneous cognitive load by facilitating information access, while also influencing germane cognitive load depending on how learners engage with AI-generated outputs. Rather than assuming a uniform effect, the model conceptualizes cognitive engagement as a mediating mechanism capturing the depth and quality of task-related cognitive processing resulting from ChatGPT use.

In addition to these theoretically grounded mechanisms, the model incorporates ChatGPT experience as an exogenous control variable directly predicting academic

Table 1 Theory hypothesis mapping for the conceptual model

Hypothesis	Structural relationship	Core construct(s)	Primary theoretical lens	Supporting theory	Theoretical rationale
H1	ChatGPT experience → Academic performance	AI familiarity, proficiency	Experiential Learning Perspective	SCT, CLT	Accumulated experience enhances strategic AI use, prompt formulation skills, and critical evaluation of outputs. Greater familiarity increases the likelihood that ChatGPT usage translates into stronger academic performance.
H2	ChatGPT usage → Academic performance	Technology use behavior	Technology Acceptance Model (TAM)	SCT	TAM posits that sustained technology usage reflects perceived usefulness and acceptance. Once adopted, AI tools enhance task efficiency and academic support, improving performance when combined with active learner engagement.
H3	ChatGPT usage → Learning outcomes	AI-supported learning	TAM	SCT	Purposeful and sustained AI use enhances access to feedback, scaffolding, and learning resources, thereby strengthening perceived learning gains and conceptual understanding.
H4	Academic performance → Learning outcomes	Performance-based mastery	Social Cognitive Theory (SCT)	CLT	SCT emphasizes mastery experiences as central to learning. Strong academic performance consolidates knowledge and reinforces skill acquisition, leading to improved learning outcomes.
H5	ChatGPT usage → Cognitive engagement (mental effort)	Cognitive engagement (germane load)	Cognitive Load Theory (CLT)	SCT	CLT suggests AI tools may reduce extraneous load while shaping germane cognitive load. ChatGPT influences the depth of processing depending on learner regulation and task structure.
H6	ChatGPT usage → Academic self-efficacy	Self-belief, agency	Social Cognitive Theory (SCT)	TAM	Successful AI-supported task completion provides mastery experiences that strengthen academic self-efficacy and confidence in managing learning tasks.
H7	Academic self-efficacy → Academic performance	Self-regulation, persistence	SCT	CLT	Higher self-efficacy promotes persistence, strategic effort allocation, and effective self-regulation, which enhance academic performance.
H8	Cognitive engagement → Academic performance	Depth of cognitive processing	CLT	SCT	Learning effectiveness depends on germane cognitive load. Deep and sustained cognitive engagement improves task understanding and academic performance.
H9	Instructor support × Cognitive engagement → Academic performance	Environmental moderation	SCT	CLT	SCT highlights environmental influences on behavior. Instructor support structures AI use, promotes reflective engagement, and strengthens the translation of mental effort into performance.

performance. Empirical analysis revealed significant performance differences across levels of ChatGPT experience, suggesting that accumulated familiarity and strategic proficiency influence academic outcomes. Conceptually, experience reflects students' accumulated exposure, skill development, and prompt-engineering competence when using generative AI tools. By including experience as a control variable, the model ensures that the structural relationships among usage, mediators, and outcomes are estimated while accounting for systematic differences attributable to varying levels of AI familiarity.

Recent empirical studies reinforce the relevance of these mechanisms. Research demonstrates that AI-supported learning improves engagement and performance when students possess strong self-efficacy and receive instructional guidance (Huang et al. [33]; [10]), while unstructured or unsupported use increases the risk of superficial learning and dependency [6, 60]. These findings justify the inclusion of both mediating and moderating pathways rather than simple direct effects.

Accordingly, the research model adopts a mechanism-based analytical design, using mediation and moderation analysis to explain *how* and *under what conditions* ChatGPT usage influences academic outcomes. This approach aligns with SCT's emphasis on indirect and conditional effects, and with CLT's focus on cognitive processing pathways, thereby offering a more nuanced explanation of AI effectiveness in higher education.

The proposed model incorporates five core constructs:

1. ChatGPT Usage.
2. Academic Self-Efficacy (Mediator 1).
3. Mental Effort (cognitive engagement) (Mediator 2).
4. Instructor Support (Moderator).
5. Academic Performance and Learning Outcomes. Students' Academic Performance framed as self-reported assessment-oriented performance, Students' Learning Outcomes is defined as perceived learning gains and understanding.

By integrating psychological, cognitive, and instructional factors, the research model provides a theoretically grounded and empirically testable framework for understanding AI-supported learning in higher education, particularly within low-resource and non-Western contexts such as Somalia. The model advances existing literature by moving beyond direct-effect assumptions and explicitly capturing the conditional and mediated processes through which ChatGPT shapes student learning outcomes.

The model illustrates the direct and indirect effects of ChatGPT usage on students' academic performance through cognitive engagement and academic self-efficacy, the moderating role of instructor support, and the direct control effect of ChatGPT experience on academic performance.

3 Methodology

3.1 Research design and sampling technique

This study employed a quantitative, cross-sectional survey design to examine the impact of ChatGPT usage on university students' academic performance, incorporating the mediating roles of academic self-efficacy and mental effort, and moderating role of instructor support. The survey-based approach enabled efficient collection of self-reported data from a dispersed student population across multiple universities.

This study was conducted in accordance with the principles of the Declaration of Helsinki. Ethical approval was received from the Institutional Review Board (MU-IRB) (MUIRB/13/25/001) of Mogadishu University. Regarding sampling, a non-probability convenience sampling approach was used, rather than the initially stated cluster sampling. The sampling frame consisted of undergraduate and postgraduate students with prior experience using ChatGPT for academic purposes. Convenience sampling was deemed appropriate due to the exploratory nature of the study and the absence of a comprehensive sampling frame of ChatGPT users within the target population, particularly in a low-resource higher education context. Additionally, this approach enabled efficient access to respondents with relevant experience using generative AI tools, which was essential for testing the proposed model. While this method may limit the generalizability of the findings, efforts were made to include participants from diverse academic levels and disciplines to enhance variability and representation. Therefore, the results should be interpreted with caution, and future studies are encouraged to employ probability-based sampling techniques to improve external validity. Participants were recruited via online platforms (WhatsApp and Facebook), which provided accessibility and broad reach across departments and universities. While some students were naturally grouped within classes or departments, these clusters were not formally sampled using probability-based methods; instead, the clusters reflect convenience-based access points. A total of 316 responses were received, with 286 valid responses after data cleaning and filtering. The final sample represents students who voluntarily participated and may not fully generalize to the entire population, which is acknowledged as a limitation in the study.

The minimum sample size was determined using G*Power 3.1, with a 0.05 margin of error, 0.95 statistical power, 0.15 effect size, and 5 predictors, yielding a minimum required sample of 138. A post-hoc power analysis confirmed that the final sample of 286 provided adequate statistical power (>0.95) for detecting medium effect sizes. (see Fig. 2).

3.2 Data collection procedure

Data was collected using an online questionnaire hosted on Kobo Collect Forms. The questionnaire link was shared through social media and institutional mailing lists to facilitate participation. Participants were informed about the study objectives, voluntary participation, anonymity, and confidentiality prior to starting the survey. Data collection occurred over a four-week period to maximize response rates. Data quality was

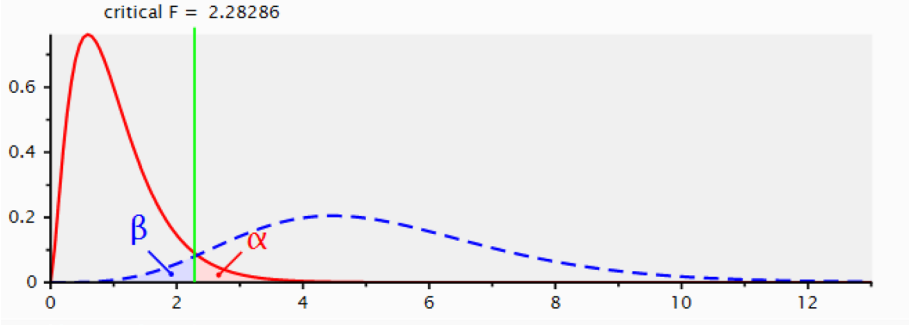


Fig. 2 Power analysis for minimum sample size

ensured by implementing validation checks in the online survey, removing incomplete responses, and addressing outliers and missing values. Responses with excessive missing data (> 10%) or inconsistent answer patterns were excluded. Common method bias was assessed using Harman's single factor test and full collinearity VIF checks, confirming that no single factor explained the majority of variance (below 50%), suggesting limited bias.

3.3 Measures and instrument development

The study measured five primary constructs using validated scales on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). All items were reviewed for content validity by two domain experts and translated into the local language using a translation-back-translation procedure to ensure semantic equivalence. Sample items and sources are summarized below:

- ChatGPT Usage: Frequency and purpose of ChatGPT utilization (e.g., "I use ChatGPT to clarify complex academic concepts"). Items were adapted from the ChatGPT Usage Scale for Foreign Language Learners [11].
- The Mental Effort (Cognitive Engagement) construct was adapted from the subjective mental effort scale originally developed by Paas [36], and later adapted by [31, 59]. Sample item: "Using ChatGPT requires me to think critically about the information provided."
- Academic Self-Efficacy: Confidence in achieving academic goals using AI tools, adapted from the General Academic Self-Efficacy Scale [53]. Sample item: "I am confident I can use ChatGPT to successfully complete my assignments."
- Instructor Support: Perceived guidance and scaffolding by instructors in integrating AI tools. Adapted from Wang et al. [54]. Sample item: "My instructors provide clear guidance on how to use ChatGPT effectively."
- Academic Performance: Self-reported grades and perceived learning effectiveness, adapted from [12]. Sample item: "Using ChatGPT has improved my academic performance."
- Learning outcome items adapted by [35].

A pilot study with 58 respondents was conducted to refine items, assess clarity, and evaluate reliability. Cronbach's alpha for all constructs exceeded 0.70, indicating strong internal consistency, and minor wording adjustments were made based on feedback to improve clarity. The full questionnaire, including all items and scales, is provided in Appendix 1.

3.4 Data analysis technique

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4. PLS-SEM was selected due to its suitability for complex research models involving multiple mediating and moderating relationships and its robustness to violations of multivariate normality [39, 42]. This approach enabled the simultaneous estimation of direct, indirect (mediated), and conditional (moderated) effects among ChatGPT usage, cognitive engagement (mental effort), academic self-efficacy, instructor support, and academic performance.

In addition to PLS-SEM, one-way analysis of variance (ANOVA) was conducted using SPSS to examine whether students' academic performance and related learning constructs differed significantly across levels of ChatGPT experience (low, moderate, and high usage). This supplementary analysis was undertaken in response to reviewer recommendations to explicitly explore heterogeneity in AI usage experience and to contextualize the structural model results. Post hoc comparisons were performed using Tukey's HSD test to identify specific group differences.

Prior to model estimation, data screening procedures were conducted, including checks for missing values, outlier detection, and assessment of distributional properties. Descriptive statistics were used to summarize participant demographics and the main study variables. Following established PLS-SEM guidelines, model evaluation was performed in two stages: first, the measurement model was assessed for reliability, convergent validity, and discriminant validity; second, the structural model was evaluated by examining path coefficients, coefficients of determination (R^2), effect sizes (f^2), predictive relevance (Q^2), and bootstrapped significance levels [17] (Ringle et al. 2020).

Finally, the use of self-reported measures of academic performance is acknowledged as a methodological limitation, as such measures may be subject to response bias. This limitation, along with its implications for interpretation is discussed.

4 Data analysis

4.1 Statistical analysis

The current study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4.1.1.1 to evaluate the proposed research model and test the hypothesized relationships. PLS-SEM was selected over covariance-based SEM approaches (e.g., AMOS) for several methodological and analytical reasons. First, the proposed model incorporates dual mediation (self-efficacy and mental effort) and a moderating effect (instructor support), resulting in a relatively complex structural configuration. PLS-SEM is particularly suitable for estimating complex predictive models with multiple mediating and moderating paths while maintaining statistical robustness [19]. In contrast, covariance-based SEM (CB-SEM) methods such as AMOS are primarily oriented toward theory confirmation and global model fit optimization, and they often require larger samples and stricter distributional assumptions.

Second, PLS-SEM is prediction-oriented and variance-based, making it appropriate when the primary objective is to explain endogenous constructs (i.e., academic performance) and maximize explained variance (R^2), rather than reproduce an empirical covariance matrix. Given that this study aims to uncover the psychological and instructional mechanisms through which ChatGPT usage influences performance, a predictive modeling approach is theoretically and analytically aligned with the research objectives.

Third, PLS-SEM is well suited for data that deviate from multivariate normality. Normality assessment indicated that the dataset significantly departed from multivariate normality based on Mardia's multivariate skewness ($\beta = 346.335$, $p < 0.001$) and kurtosis ($\beta = 54.45817$, $p < 0.001$), as evaluated using the Web Power online tool. Because CB-SEM relies heavily on multivariate normality assumptions for maximum likelihood estimation, violations of normality may bias parameter estimates and fit indices. In contrast, PLS-SEM does not require normally distributed data and therefore provides more stable and reliable estimates under non-normal conditions.

Furthermore, recent methodological studies in educational technology research have recommended PLS-SEM for examining emerging digital learning environments characterized by complex interrelationships and exploratory theory extension. For example, Soliman et al. [47] employed PLS-SEM to model continuous intention to use the metaverse as a learning platform, emphasizing its suitability for analyzing technology adoption models with moderating effects and predictive orientations. Consistent with this methodological precedent, the present study adopts PLS-SEM to examine AI-mediated learning mechanisms involving mediation and moderation within a single integrated framework.

The analysis followed the recommended two-step approach: (1) assessment of the measurement model to evaluate reliability and validity of the constructs, and (2) assessment of the structural model to test the hypothesized relationships, mediation, and moderation effects.

4.2 Common method bias

The common method bias (CMB) was assessed using the Variance Inflation Factor (VIF) values of the inner model, as recommended in prior literature to detect potential multicollinearity issues. In this study, all VIF values ranged between 1.090 and 2.512, which fall well below the acceptable threshold of 3.33 [26]. This indicates that there is no substantial collinearity between the constructions, suggesting that common method bias is not a concern in this model. Hence, the results can be considered reliable and free from significant common method bias. (See Table 2)

Table 2 Profile data

		Frequency	Percentage (%)
Gender	Female	92	32.2
	Male	194	67.8
Age	Below 18	17	5.9
	18–22	160	55.9
	23–27	80	28.0
	28–32	13	4.5
	Above 32	16	5.6
Academic year	First year (freshman)	79	27.6
	Second year (sophomore)	32	11.2
	Third year (junior)	53	18.5
	Fourth Year (senior)	66	23.1
	Postgraduate (master's/PhD)	56	19.6
Field of study/major	Computer Science / IT	73	25.5
	Engineering	10	3.5
	Business & Management	60	21.0
	Health & Medicine	22	7.7
	Social Sciences & Humanities	32	11.2
	Education	18	6.3
	Others (Specify):	71	24.8
Have you used AI-based learning tools (ChatGPT, Bard, etc.) before?	Yes, frequently	175	61.2
	Yes, but occasionally	84	29.4
	No, but I am aware of them	18	6.3
	No, I have never used them	9	3.1

Table 3 One-way ANOVA examining differences in students' academic performance across levels of ChatGPT experience

Variable	ChatGPT experience level	*N*	Mean	SD	ANOVA F (df)	*p*-value	Post-hoc (Tukey HSD)
Academic performance	Low experience	92	2.57	0.85			
	Moderate experience	80	3.35	0.75	88.12 (2, 283)	< 0.001	Moderate > Low***
	High experience	114	3.94	0.62			High > Moderate***
							High > Low***

Low, moderate, and high ChatGPT experience groups were compared using one-way ANOVA. Levene's test indicated a violation of the homogeneity of variances assumption ($p < 0.05$); however, given the large and unequal group sizes, the ANOVA was considered robust. Post-hoc comparisons were conducted using Tukey's HSD test. ***$p < 0.001$

4.3 Profile of the respondents

The demographic profile of the respondents indicates a diverse sample in terms of gender, age, academic year, field of study, and familiarity with AI-based learning tools. The majority were male (67.8%), while females comprised 32.2%. Most respondents (55.9%) were aged between 18 and 22 years, followed by 28.0% aged 23–27 years, with smaller proportions in other age groups. In terms of academic year, 27.6% were first-year students, 23.1% were fourth-year, 18.5% were third-year, 11.2% were second-year, and 19.6% were postgraduate students. The most represented fields of study were Computer Science/IT (25.5%) and Business & Management (21.0%), with smaller percentages in Social Sciences & Humanities, Health & Medicine, Education, Engineering, and a diverse "Others" category (24.8%). Regarding AI-based learning tools, 61.2% reported using them frequently, 29.4% occasionally, while 6.3% were aware but had never used them, and 3.1% had no experience. This data suggests a predominantly young, technology-oriented sample with substantial engagement in AI tools and a broad representation across academic disciplines and years. The results are presented in Table 2.

4.4 Differences across levels of ChatGPT experience

To further contextualize the findings, a one-way ANOVA was conducted to examine whether academic performance differed across levels of ChatGPT experience (low, moderate, and high). Descriptive results showed a clear increasing trend in performance from low ($M = 2.57$, SD = 0.85) to moderate ($M = 3.35$, SD = 0.75) and high experience groups ($M = 3.94$, SD = 0.62). The ANOVA revealed a significant group effect, $F(2, 283) = 88.12$, $p < 0.001$. Post-hoc Tukey tests indicated that all pairwise differences were statistically significant, with students in the high-experience group outperforming both moderate and low experience groups. These findings suggest that the academic benefits associated with ChatGPT use are not uniform but increase substantially with greater user experience. The result represented in the Table 3.

4.5 Incorporating ChatGPT experience into the structural model

Given the significant differences observed across levels of ChatGPT experience, the variable was incorporated into the structural equation model to ensure alignment between descriptive and inferential analyses. Experience was specified as an exogenous predictor directly influencing academic performance. The extended model indicated that ChatGPT experience had a significant positive direct effect on academic performance. Importantly, the inclusion of experience did not materially alter the direction or significance of the hypothesized structural paths. ChatGPT usage remained significantly

Table 4 Outer loadings, reliability, convergent validity and VIF

Constructors	Items	Outer loadings	Alpha	CR	AVE	VIF
ChatGPT usage	PUC1	0.714	0.862	0.862	0.55	1.938
	PUC2	0.746				1.903
	PUC3	0.754				1.847
	PUC4	0.737				1.850
	PUC5	0.772				1.936
Cognitive engagement (mental effort)	PME1	0.825	0.768	0.779	0.526	1.495
	PME2	0.707				1.651
	PME4	0.630				1.577
Perceived instructor support	PIS1	0.777	0.866	0.867	0.563	2.037
	PIS2	0.793				2.434
	PIS3	0.718				2.324
	PIS4	0.714				1.905
	PIS5	0.746				1.627
Perceived self-efficacy	PSEF1	0.812	0.868	0.871	0.568	1.897
	PSEF2	0.787				2.033
	PSEF3	0.751				1.865
	PSEF4	0.763				2.317
	PSEF5	0.646				1.856
Students' learning outcomes	SLO1	0.748	0.876	0.877	0.587	1.794
	SLO2	0.766				2.096
	SLO3	0.785				2.512
	SLO4	0.738				2.236
	SLO5	0.791				1.090
Students' academic performance	SAP1	0.730	0.869	0.869	0.570	1.944
	SAP2	0.742				1.796
	SAP3	0.755				1.987
	SAP4	0.780				2.211
	SAP5	0.766				2.088

associated with cognitive engagement and academic self-efficacy, and both mediators retained their explanatory roles. These findings suggest that experience enhances performance independently but does not replace the psychological mechanisms through which ChatGPT usage influences outcomes. Rather than functioning as a mediator, experience operates as a conditioning factor that strengthens students' ability to derive academic benefits from AI-supported learning.

4.6 Measurement model evaluation

The measurement model was evaluated using indicator reliability, internal consistency reliability, convergent validity, discriminant validity, and collinearity diagnostics. Indicator reliability was assessed through outer loadings, which ranged from 0.630 to 0.825, exceeding the minimum acceptable threshold of 0.60. Although two indicators (PME4 = 0.630; PSEF5 = 0.646) exhibited comparatively lower loadings, they were retained to preserve content validity and conceptual breadth, as they capture theoretically meaningful subdimensions of cognitive engagement and academic self-efficacy. Importantly, retaining these items did not adversely affect construct reliability or convergent validity, consistent with theory-driven PLS-SEM measurement practices [17, 42]. Moreover, indicators with low factor loadings (< 0.60) were removed [16]. The items PME3 and PME5 were removed from the analysis due to low factor loading. Internal consistency reliability was confirmed, with Cronbach's alpha values ranging from 0.768 to 0.876 and

Table 5 Discriminant validity Fornell–Lacker criterion

	SAP	SLO	PME	PSEF	PIS	PUC
Students' academic performance	0.755					
Students' learning outcome	0.894	0.766				
Mental effort	0.788	0.762	0.725			
Perceived self-efficacy	0.888	0.869	0.766	0.754		
Perceived instructor support	0.765	0.708	0.8	0.638	0.75	
ChatGPT usage	0.782	0.759	0.856	0.78	0.664	0.745

Table 6 Discriminant validity heterotrait–monotrait ratio (HTMT)

Students' academic performance	SAP	SLO	PME	PSEF	PIS	PUC
Students' learning outcome	0.894					
Mental effort	0.785	0.762				
Perceived self-efficacy	0.886	0.865	0.765			
Perceived instructor support	0.764	0.708	0.803	0.635		
ChatGPT usage	0.782	0.758	0.85	0.782	0.663	

composite reliability (CR) values ranging from 0.779 to 0.877, all exceeding the recommended threshold of 0.70 (Ringle et al. 2020). Convergent validity was assessed using the average variance extracted (AVE), with values between 0.526 and 0.587, surpassing the recommended minimum of 0.50 [42]. These results indicate that all constructs explain more than half of the variance in their respective indicators. In addition, variance inflation factor (VIF) values were below 3.3 for all indicators, suggesting that multicollinearity is not a concern.(see Table 3; Fig. 2).

Discriminant validity was assessed using both the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio (see Tables 4 and 5). While most construct pairs satisfied discriminant validity requirements, an important exception emerged between Students' Academic Performance and Students' Learning Outcomes. Specifically, the correlation between these constructs ($r = 0.894$) exceeded the square roots of their AVEs (0.755 and 0.766, respectively), indicating that the Fornell–Larcker criterion is not satisfied for this construct pair [15]. This result suggests substantial conceptual overlap between academic performance and learning outcomes. This finding is theoretically plausible, as both constructs reflect closely related aspects of academic achievement. However, they were intentionally retained as distinct constructs to capture different analytical levels: academic performance reflects students' self-reported achievement outcomes (e.g., grades and task performance), whereas *learning outcomes* capture broader perceptions of knowledge acquisition, understanding, and skill development. Similar distinctions between performance-based and perception-based outcomes have been maintained in prior educational technology research, despite high correlations, when supported by theory and research objectives.

The HTMT value between academic performance and learning outcomes (HTMT = 0.894) approaches, but does not exceed, the conservative threshold of 0.90 [63], further indicating that discriminant validity between these constructs is borderline rather than fully violated. Following recent methodological guidance, this result warrants cautious interpretation rather than automatic construct elimination [19]. Accordingly, subsequent structural results involving these two constructs are interpreted conservatively, and their conceptual proximity is explicitly acknowledged in the discussion section.

Overall, the measurement model demonstrates satisfactory indicator reliability, internal consistency, and convergent validity. Discriminate validity is supported for most constructs, with a noted and transparently reported exception between academic performance and learning outcomes, which is theoretically justified and appropriately qualified in interpretation (Fig. 3).

4.7 Evaluating inner structure model

The structural model was evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM) with a bootstrapping procedure of 10,000 resamples, which provides robust estimates of standard errors and confidence intervals for hypothesis testing. PLS-SEM was selected due to its suitability for theory development, complex models with mediating and moderating relationships, and non-normal data, consistent with recent methodological recommendations in higher education and digital learning research (Ali et al. 2025). The results of the direct structural paths are reported in Table 6. ChatGPT usage demonstrated a significant positive effect on learning outcomes ($\beta = 0.523$, $p < 0.01$), indicating that students who actively use ChatGPT as a learning support tool report higher perceived learning gains. This finding is consistent with prior AI-supported learning research emphasizing accessibility, feedback immediacy, and scaffolding effects. Academic performance exerted a strong positive influence on learning outcomes ($\beta = 0.894$, $p < 0.001$), confirming that performance remains a central mechanism through which learning outcomes are realized, in line with Social Cognitive Theory and performance-based learning models.

ChatGPT usage was also found to significantly predict both mental effort (cognitive engagement) ($\beta = 0.811$, $p < 0.001$) and academic self-efficacy ($\beta = 0.781$, $p < 0.001$). Importantly, this result should not be interpreted as ChatGPT uniformly increasing

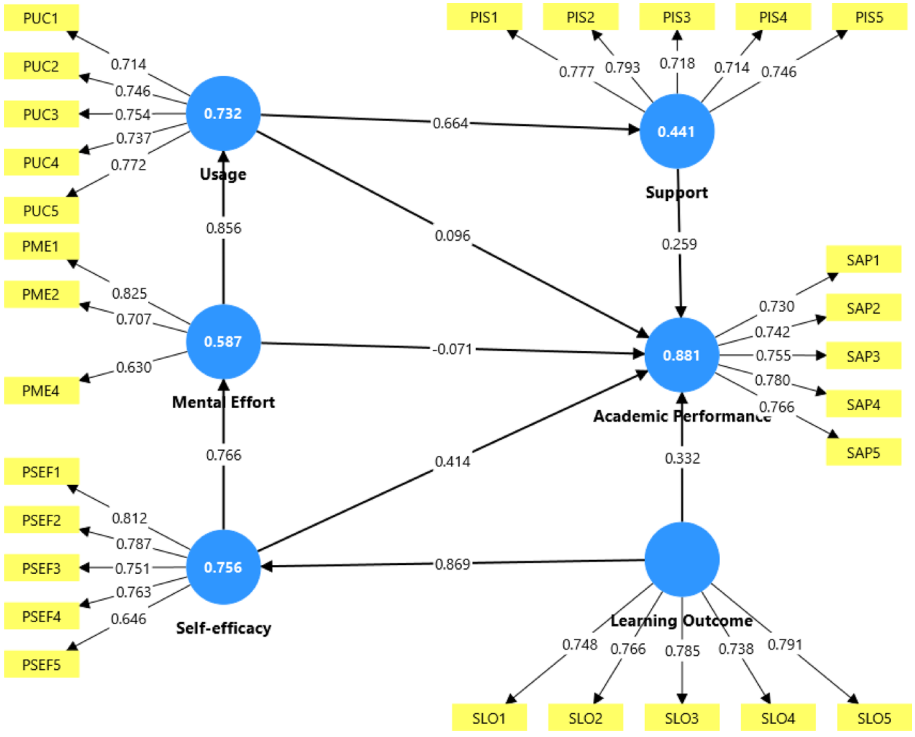


Fig. 3 Measurement model

Table 7 Structural model

Hypotheses	Relationship	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	*P* values
H2	Usage ChatGPT → academic performance	0.184	0.191	0.281	0.655	0.513
H3	Usage ChatGPT → learning outcome	0.523	0.516	0.162	3.217	0.001
H4	Academic performance → learning outcome	0.894	0.895	0.03	29.469	< 0.001
H5	Usage ChatGPT → cognitive engagement (mental effort)	0.811	0.814	0.046	17.717	< 0.001
H6	Usage ChatGPT → self-efficacy	0.781	0.783	0.047	16.465	< 0.001

cognitive load. Rather, consistent with Cognitive Load Theory, ChatGPT appears to shape the quality and allocation of mental effort, particularly germane cognitive engagement, when students interact actively with the system.

In contrast, the direct path from ChatGPT usage to academic performance was not statistically significant ($\beta = 0.184$, $p = 0.513$). This non-significant relationship suggests that ChatGPT does not directly translate into improved academic performance, reinforcing the theoretical argument that AI tools influence performance indirectly through psychological and cognitive mechanisms, rather than functioning as performance-enhancing technologies per se. The result presented in the Table 6.

4.8 Mediating analysis

A mediation analysis was conducted to examine the psychological and cognitive mechanisms through which ChatGPT usage influences students' academic performance. Consistent with Social Cognitive Theory (SCT) and Cognitive Load Theory (CLT), academic self-efficacy and cognitive engagement were specified as parallel mediators in the relationship between ChatGPT usage and academic performance. The structural model included the paths from ChatGPT usage to each mediator (a-paths), from each mediator to academic performance (b-paths), the direct effect of ChatGPT usage on academic performance (c′-path), and the corresponding indirect effects.

The model was estimated using PLS-SEM with a bootstrapping procedure of 10,000 resamples. Bias-corrected 95% confidence intervals (CIs), standard errors, and t-values were computed for all direct and indirect effects. Mediation was evaluated by examining the statistical significance of indirect effects in conjunction with the residual direct effect (c′).

Academic Self-Efficacy as Mediator (H7). The results indicate that ChatGPT usage positively and significantly predicts academic self-efficacy (a_1-path: $\beta = 0.673$, $p < 0.001$). Academic self-efficacy, in turn, positively and significantly predicts academic performance (b_1-path: $\beta = 0.786$, $p < 0.001$). When both mediators were included in the model, the direct effect of ChatGPT usage on academic performance was non-significant (c′-path: $\beta = 0.041$, $p = 0.612$).

The bootstrapped indirect effect of ChatGPT usage on academic performance through academic self-efficacy was significant ($\beta = 0.529$, STDEV = 0.102, t = 5.186, $p < 0.001$), and the 95% confidence interval did not include zero. Taken together, these findings indicate full mediation. ChatGPT usage influences academic performance indirectly through its

positive effect on academic self-efficacy, rather than exerting a significant direct impact. In line with SCT, this suggests that AI-supported interactions enhance students' perceived competence and self-regulatory confidence, which subsequently translate into improved academic outcomes. Cognitive Engagement as Mediator (H8), ChatGPT usage was found to significantly predict cognitive engagement (a_2-path: $\beta = 0.412$, $p < 0.01$), indicating that AI usage increases reported mental effort. However, cognitive engagement did not significantly predict academic performance (b_2-path: $\beta = -0.311$, $p = 0.284$). Accordingly, the indirect effect of ChatGPT usage on academic performance through cognitive engagement was not statistically significant ($\beta = -0.128$, STDEV = 0.388, t = 0.33, $p = 0.741$), and the corresponding confidence interval included zero. H8 is therefore not supported. Although ChatGPT usage increases cognitive engagement, this engagement does not translate into improved academic performance within the present model. From a CLT perspective, this pattern suggests that increased mental effort may reflect extraneous or inefficient cognitive load rather than germane cognitive processing that contributes to performance gains (see Table 7).

4.9 Moderating analysis

A moderation analysis was conducted to examine whether instructor support conditions the relationship between cognitive engagement and academic performance. The interaction effect was tested within the PLS-SEM framework by creating a product indicator term between instructor support and cognitive engagement. All predictor variables were mean-centered prior to constructing the interaction term to reduce potential multicollinearity. The structural model therefore included (1) the main effect of cognitive engagement on academic performance, (2) the main effect of instructor support on academic performance, and (3) the interaction term (Instructor Support × Cognitive Engagement) predicting academic performance. Bootstrapping with 10,000 resamples was applied to estimate standard errors, t-values, p-values, and bias-corrected 95% confidence intervals for the interaction effect.

The results indicate that the interaction term is positive and statistically significant ($\beta = 0.079$, STDEV = 0.039, t = 2.055, $p = 0.040$). The 95% confidence interval did not include zero, supporting H9. This finding demonstrates that instructor support significantly moderates the relationship between cognitive engagement and academic performance. To interpret the interaction, a simple slope analysis was conducted. The results show that when perceived instructor support is high (+ 1 SD), the relationship between cognitive engagement and academic performance becomes positive and stronger. In contrast, when instructor support is low (– 1 SD), the relationship between cognitive engagement and academic performance remains weak and non-significant. This pattern

Table 8 Mediation analysis

Hypotheses	Relationship	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	*P* values
H7	Usage ChatGPT → self-efficacy → academic performance	0.529	0.532	0.102	5.186	< 0.001
H8	Usage ChatGPT → cognitive engagement → academic performance	-0.128	-0.148	0.388	0.33	0.741

indicates that cognitive engagement translates into improved academic performance only under conditions of adequate instructional support.

Although the magnitude of the interaction effect is modest (β = 0.079), its direction and statistical significance suggest a meaningful contextual effect. The findings indicate that cognitive engagement alone is insufficient to enhance performance outcomes. Rather, instructional scaffolding strengthens the alignment between students' cognitive investment and academic objectives. These results underscore the conditional nature of AI-supported learning. Instructor support appears to function as a pedagogical amplifier, enabling students' cognitive engagement to contribute more effectively to academic achievement. In the absence of such support, increased engagement may not yield proportional performance benefits. This interpretation is consistent with research emphasizing that the educational value of digital technologies depends not only on individual usage behaviors but also on structured instructional guidance and supportive learning environments. (See Table 8)

4.10 Structural model evaluation and predictive assessment

The evaluation of the structural model was extended beyond path coefficients and significance testing to include explanatory power (R^2), predictive relevance (Q^2), and effect size estimates (f^2) for key relationships [17, 42]. The coefficient of determination (R^2) was examined for all endogenous constructs to assess the model's explanatory capability. As shown in Table 10, ChatGPT usage explains a substantial proportion of variance in mental effort (R^2 = 0.658) and self-efficacy (R^2 = 0.611), indicating strong explanatory power. Academic performance is jointly explained by ChatGPT usage, self-efficacy, cognitive engagement, and instructor support, yielding a high R^2 value of 0.859, while learning outcomes demonstrate a strong dependence on academic performance (R^2 = 0.800). According to established benchmarks, these values indicate moderate to substantial explanatory power [18]. Predictive relevance was assessed using the blindfolding procedure. All endogenous constructs exhibited Q^2 values greater than zero, confirming that the model possesses adequate out-of-sample predictive relevance. This finding indicates that the proposed model not only explains observed relationships but also has meaningful predictive capability, thereby reducing concerns related to overfitting [20]. To complement statistical significance testing, Cohen's f^2 effect sizes were calculated to assess the substantive impact of each exogenous construct on endogenous variables. The results indicate that ChatGPT usage exerts a large effect on mental effort and self-efficacy, a moderate effect on learning outcomes, and a negligible direct effect on academic performance. In contrast, self-efficacy demonstrates a strong effect on academic performance, while the interaction term (Instructor Support × Cognitive Engagement) shows a small but meaningful moderating effect. These results further support the conclusion that ChatGPT influences academic performance primarily through indirect and conditional pathways rather than direct effects. (see Table 9).

Table 9 Moderating analysis

Hypothesis	Relationship	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	*P* values
H9	Instructor support × mental effort → academic performance	0.079	0.079	0.039	2.055	0.04

Table 10 Predictive accuracy and effect sizes of the structural model

Endogenous construct	R^2	R^2 Adjusted	Q^2	Key predictors	f^2 (effect size)
Cognitive engagement	0.658	0.656	> 0	ChatGPT usage	Large
Self-efficacy	0.611	0.609	> 0	ChatGPT usage	Large
Academic performance	0.859	0.857	> 0	Self-efficacy	Large
				Cognitive engagement	Small
				ChatGPT usage	Negligible
				Instructor support × cognitive engagement	Small
Learning outcomes	0.800	0.799	> 0	Academic performance	Large

Table 11 Model fit

SRMR	Saturated model	Estimated model
	0.056	0.057
d_ULS	1.461	1.505
d_G	0.59	0.594
Chi-square	945.991	950.7
NFI	0.815	0.814

SRMR, Standardized root means square residual; NFI, normed fit index

4.11 Assessment of model fit

The global fit of the proposed structural model was evaluated using multiple goodness-of-fit indices in accordance with established PLS-SEM guidelines [17, 20]. As reported in Table 9, the standardized root mean square residual (SRMR) values for both the saturated model (0.056) and the estimated model (0.057) fall below the recommended threshold of 0.08, indicating an acceptable overall model fit. The negligible difference between the two SRMR values suggests that the imposed structural constraints did not distort the model, thereby mitigating concerns related to overfitting. Additional discrepancy measures further support the adequacy of the model. The d_ULS and d_G values are highly comparable between the saturated (d_ULS = 1.461; d_G = 0.590) and estimated models (d_ULS = 1.505; d_G = 0.594), indicating low residual variance and stable parameter estimation.

Finally, the normed fit index (NFI) values for the saturated (0.815) and estimated (0.814) models exceed the minimum acceptable level for PLS-SEM applications, reflecting adequate incremental fit relative to a null model [18]. Collectively, these indices demonstrate that the proposed model exhibits satisfactory global fit and provides a robust foundation for interpreting the structural, mediation, and moderation effect. (see Table 10).

5 Discussion

This study investigated how ChatGPT usage influences students' academic performance and learning outcomes through the mediating roles of academic self-efficacy and cognitive engagement (mental effort), as well as the moderating role of instructor support, within a low-resource higher education context. In addition, following significant ANOVA findings, ChatGPT experience was incorporated into the structural model as an influencing factor on academic performance. By integrating Social Cognitive Theory (SCT), Cognitive Load Theory (CLT), and the Technology Acceptance Model (TAM), the findings provide a nuanced explanation of the mediated, moderated, and experience

conditioned effects of generative AI on learning. Importantly, this study contributes to the emerging AI in education literature by offering context-sensitive evidence from a low-resource setting, where the role of generative AI differs fundamentally from that observed in well-resourced educational systems.

A central finding is that ChatGPT usage did not exert a statistically significant direct effect on academic performance, despite positively influencing learning outcomes, self-efficacy, and cognitive engagement. This result aligns with recent international evidence showing that generative AI tools do not automatically translate into improved academic performance [24, 61]. Academic performance reflects sustained mastery, assessment alignment, and self-regulated learning, which are unlikely to be driven by technology use alone. Instead, AI functions as an enabling resource whose impact depends on psychological and instructional mechanisms. This finding is consist with recently studies [38, 45], which highlight that AI's educational value emerges through complex, non-linear pathways rather than direct effects on performance.

In the Somali context, where ChatGPT often substitutes for limited academic resources rather than supplementing established learning systems, students primarily use AI for information access and clarification. While this enhances perceived learning and confidence, it does not necessarily improve grades unless supported by structured instructional design and assessment-oriented practices. Similar patterns have been reported in studies from Indonesia, China, and the Philippines, where AI-assisted learning improved engagement and perceived learning but showed weaker or indirect effects on performance [27, 29, 64]. However, unlike prior studies conducted in relatively better-resourced environments, this study uniquely demonstrates that in low resource contexts, generative AI assumes a compensatory role filling systemic gaps in access to academic materials, guidance, and feedback thereby reshaping the pathways through which learning outcomes are achieved.

The mediation analysis clarifies this pattern. Academic self-efficacy emerged as a significant mediator, indicating that ChatGPT contributes to academic performance primarily by strengthening students' beliefs in their academic capabilities. This finding is consistent with SCT, which emphasizes mastery experiences and perceived competence as key mechanisms linking learning tools to achievement [7, 56]. When students successfully complete tasks with AI assistance, their perceived competence increases, which in turn enhances persistence, strategic regulation, and performance.

In contrast, cognitive engagement did not independently mediate the ChatGPT–performance relationship. This suggests that effort alone is insufficient unless directed toward germane cognitive processing, as emphasized in CLT [66]. Without appropriate structuring, students may expend effort reading or interacting with AI outputs without engaging in deeper conceptual processing. This distinction highlights the importance of differentiating between surface-level effort and meaningful cognitive investment. This finding contributes to the literature by empirically demonstrating that engagement, in the absence of instructional scaffolding, may remain inefficient in resource-constrained environments where students lack complementary academic support systems.

Importantly, ChatGPT experience emerged as a significant direct predictor of academic performance. Students with greater accumulated experience demonstrated stronger performance outcomes, independent of usage frequency. This finding suggests that familiarity, strategic prompting ability, and critical evaluation skills develop over

time and enhance students' capacity to leverage AI effectively. From an SCT perspective, repeated successful interactions with AI may reinforce mastery experiences and self-regulatory confidence. From a CLT perspective, experienced users may manage cognitive load more efficiently by formulating clearer prompts and filtering irrelevant outputs. Thus, while experience does not replace the mediating roles of self-efficacy and cognitive engagement, it strengthens students' ability to translate AI use into academic gains. Notably, this highlights a novel contribution: in low-resource contexts, experiential learning with AI tools may substitute for formal digital literacy training, positioning experience as a critical pathway to performance enhancement.

The moderation analysis provides a crucial integrate insight by showing that instructor support significantly conditions the relationship between cognitive engagement and academic performance. Cognitive engagement contributes to performance only when supported by instructional guidance, feedback, and task structuring. This finding is consistent with prior research demonstrating that instructor presence enhances the effectiveness of digital and AI-supported learning environments [9, 25]. From a TAM perspective, instructor support also shapes the perceived usefulness of ChatGPT by enabling purposeful and pedagogically aligned use. This finding extends prior AI adoption models by demonstrating that institutional and pedagogical factors not only influence usage intentions but also critically determine the effectiveness of actual AI use in producing academic outcomes.

The moderating effect of instructor support can be interpreted in concrete pedagogical terms. Instructor behaviors such as establishing clear AI usage guidelines, designing tasks that require critical evaluation of AI-generated responses, and providing formative feedback on how students integrate ChatGPT outputs into their reasoning directly shape how mental effort is invested. For example, when instructors require students to compare AI-generated answers with course materials, justify modifications, or reflect on discrepancies, cognitive engagement is redirected toward germane processing rather than passive acceptance. Assessment designs that prioritize explanation, argumentation, and application over reproduction further reduce the likelihood that AI substitutes for thinking and instead encourage meaningful knowledge construction.

Feedback mechanisms further strengthen this translation process. When instructors comment not only on final answers but also on students' reasoning processes including how they used ChatGPT, what they accepted or rejected, and why mental effort becomes metacognitively structured. Such feedback reinforces self-regulation and helps students calibrate trust in AI outputs. In low-resource contexts, where independent academic scaffolding may be limited, this instructional mediation is especially critical. Without it, cognitive effort may remain surface-level, whereas structured guidance transforms effort into deeper conceptual understanding more likely to influence performance. This underlines a key contextual contribution: in environments with limited institutional resources, instructor support becomes a central mechanism for transforming AI from a basic information tool into a catalyst for higher-order learning.

Overall, the findings present a consistent picture: ChatGPT enhances academic outcomes indirectly through self-efficacy and through cognitive engagement under supportive instructional conditions, while accumulated experience strengthens students' ability to derive performance benefits from AI use. Instructor behaviors particularly AI-integrated task design, explicit usage norms, and formative feedback serve as catalytic

mechanisms that convert cognitive effort into measurable academic performance. By situating these findings within a low-resource higher education context, this study makes a distinct contribution to AI-in-education research by demonstrating that the effectiveness of generative AI is not universal but highly context-dependent, shaped by resource availability, instructional practices, and students' adaptive learning strategies. In low-resource contexts such as Somalia, both instructional support and strategic AI experience are critical in ensuring that generative AI fosters meaningful learning rather than superficial task completion.

Implication of the study.

5.1 Theoretical implications

This study advances the AI-in-education literature by moving beyond deterministic assumptions that generative AI usage directly improves academic performance. Rather than treating ChatGPT as a uniformly beneficial instructional innovation, the findings demonstrate that its impact is conditional upon psychological and instructional mechanisms. This represents a theoretical shift from "technology-as-driver" models toward a mechanism-based explanation of AI-supported learning.

The study contributes to Cognitive Load Theory (CLT) by refining how mental effort is conceptualized in AI-mediated environments. While prior literature often assumes that AI reduces cognitive load in a beneficial manner, the present findings demonstrate that reduced mental effort does not automatically translate into improved academic performance. Instead, cognitive engagement contributes to performance only under supportive instructional conditions. This extends CLT by emphasizing that the quality and direction of mental effort—rather than its mere reduction—determine learning effectiveness in generative AI contexts.

From a Social Cognitive Theory (SCT) perspective, the study provides empirical evidence that ChatGPT usage enhances academic performance indirectly through self-efficacy. This extends SCT into AI-mediated learning environments by showing that generative AI tools function as belief-shaping resources that influence self-regulatory confidence rather than as direct performance enhancers. By identifying self-efficacy as a central mediating mechanism, the study clarifies why AI usage may improve perceived learning without necessarily improving grades unless psychological empowerment occurs.

Regarding the Technology Acceptance Model (TAM), this research makes a novel contribution by repositioning TAM from an adoption-focused framework to a post-adoption explanatory bridge. Rather than re-testing traditional TAM constructs (perceived usefulness and ease of use), the study treats ChatGPT usage as a behavioral proxy for prior acceptance and focuses analytically on what happens after adoption. This extends TAM by embedding it within a broader mechanism-based framework that links technology usage to psychological and cognitive mediators. In doing so, the study integrates TAM, SCT, and CLT into a coherent explanatory chain that connects behavioral adoption, belief formation, cognitive processing, and instructional context.

Collectively, the study's primary theoretical novelty lies in its dual-mediation and moderated framework tested within a low-resource higher education context. By empirically demonstrating that instructor support conditions the translation of cognitive engagement into performance, the research highlights the socio-instructional contingencies of

generative AI effectiveness an area underexplored in current AI-in-education scholarship dominated by high-income settings.

5.2 Practical implications

Practically, the study provides actionable insights for educational institutions, policymakers, and educators. The findings confirm that incorporating AI tools like ChatGPT can enhance learning outcomes and strengthen student self-efficacy but only when pedagogically structured.

First, institutions should move beyond permissive or restrictive AI policies and instead develop clear AI usage guidelines that articulate when and how ChatGPT should be used. Structured guidelines such as requiring students to document prompts, critically evaluate AI responses, and explain how outputs were adapted can transform passive usage into reflective learning.

Second, task design must be intentionally aligned with higher-order cognitive objectives. Assignments should require comparison between AI-generated responses and course materials, justification of modifications, and application to novel scenarios. Such design strategies ensure that mental effort is directed toward germane processing rather than simple reproduction. Assessment formats that emphasize reasoning, synthesis, and argumentation further reduce the likelihood of superficial AI dependency.

Third, formative feedback plays a pivotal role. Instructors should provide process-oriented feedback that evaluates not only final answers but also how students used ChatGPT what they accepted, rejected, or revised, and why. This metacognitive scaffolding strengthens self-regulation and helps calibrate students' trust in AI outputs. Faculty development programs should therefore train instructors not only in technical AI use, but also in AI-integrated pedagogical strategies.

For educational leaders, the significant moderating role of instructor support suggests that AI adoption strategies should prioritize blended learning models. AI tools should complement not replace human instructional guidance. Investments in faculty capacity-building, AI literacy workshops, and curriculum redesign are essential to maximize learning benefits.

For policymakers, the findings underscore the importance of developing ethical and pedagogical frameworks for AI integration. Rather than focusing solely on access or prohibition, policy initiatives should encourage structured AI integration models that combine technological infrastructure, instructor training, and assessment reform.

The study also emphasizes that educational strategies should foster student self-efficacy alongside responsible AI use. Institutions should invest in both technological infrastructure and human capital development to ensure that AI-supported learning remains student-centered and cognitively engaging.

Overall, the practical implication is clear: generative AI enhances academic performance not through autonomous deployment, but through carefully designed instructional ecosystems where guidelines, task structures, and feedback mechanisms convert cognitive effort into meaningful achievement.

5.3 Limitations and future research

This study has several limitations that should be acknowledged. First, it employed a cross-sectional survey design, which restricts the ability to establish causal relationships

between ChatGPT usage and academic outcomes. As data were collected at a single point in time, observed associations may reflect contemporaneous perceptions rather than developmental or causal effects. Cross-sectional mediation models, while statistically informative, cannot definitively establish temporal ordering among usage, self-efficacy, cognitive engagement, and performance. Consequently, the indirect effects identified in this study should be interpreted as associative rather than strictly causal pathways. Future research should employ longitudinal, experimental, or quasi-experimental designs to better capture changes in self-efficacy, cognitive engagement, and performance over time and to strengthen causal inference.

Second, the study relied primarily on self-reported measures, including students' academic performance and learning outcomes, which may be subject to social desirability bias, common method variance, and inaccuracies in self-assessment. Self-reported academic performance, in particular, may inflate or attenuate effect sizes due to perceptual bias. Students who report high ChatGPT usage or strong self-efficacy may also overestimate their academic achievement, potentially leading to artificially strengthened correlations among constructs. Conversely, self-report error may attenuate structural path coefficients if students inaccurately recall or evaluate their performance. Although procedural remedies and statistical checks were applied, the reliance on perceptual measures introduces the possibility that mediation effects especially the indirect paths through self-efficacy may partially reflect shared method variance rather than purely behavioral outcomes.

Importantly, the use of subjective performance indicators may influence the magnitude and significance of both direct and indirect effects in SEM analysis. Mediation effects are particularly sensitive to measurement precision; if the outcome variable contains systematic self-report bias, the strength of the indirect pathways may be either overstated or understated. Therefore, the non-significant direct effect of ChatGPT usage on academic performance observed in this study should be interpreted cautiously, as objective performance data may yield different effect patterns.

Future studies should triangulate self-reported measures with objective indicators such as official grade records, standardized assessment scores, learning analytics data, assignment rubrics, or system-generated usage logs. Combining perceptual and objective performance measures would allow researchers to test whether AI usage differentially predicts perceived versus actual academic achievement, thereby enhancing the robustness of mediation and moderation analyses.

Third, the methodology was purely quantitative, which constrains deeper insight into how and why students engage with ChatGPT in specific learning contexts. The lack of qualitative evidence (e.g., interviews, focus groups, or reflective journals) limits understanding of students' reasoning processes, ethical concerns, and task-level strategies when using generative AI. Future research would benefit from mixed-methods designs that combine SEM-based modeling with qualitative inquiry to enrich theoretical interpretation and clarify how cognitive engagement unfolds during AI-supported tasks.

Fourth, although a relatively robust sample size was obtained (286 valid responses), the sampling approach was non-probabilistic and context-specific, which limits generalizability. Data were collected exclusively from university students in Somalia, a low-resource higher education context where ChatGPT often substitutes for limited instructional resources rather than supplementing them. Consequently, the findings may

not fully generalize to institutions in high-income or highly digitized systems. Future studies should adopt stratified or probability-based sampling strategies across multiple universities or countries to improve representativeness and external validity.

Fifth, while the model incorporated key mediators and a moderator, other potentially influential variables such as prior AI experience, digital literacy, intrinsic motivation, disciplinary differences, and assessment type were not included. These omitted variables may act as boundary conditions that alter the magnitude of mediation and moderation effects. Future research could employ multi-group analysis (MGA) to examine whether the structural relationships differ across demographic groups (e.g., gender, field of study, year level) or levels of AI familiarity. Moreover, Although ChatGPT experience was incorporated as a direct predictor, future research could examine whether experience moderates specific structural paths (e.g., usage → cognitive engagement) to further refine understanding of experience-conditioned AI learning processes.

Looking forward, future studies should also consider emerging trends in generative AI, including multimodal AI models (text–image–audio), adaptive tutoring systems, and institutionally integrated AI platforms, to examine whether their cognitive and motivational impacts differ from text-based tools like ChatGPT. Additionally, greater attention should be paid to institutional and policy-level factors, including AI governance frameworks, instructor training programs, and ethical guidelines, particularly in developing-country contexts. Incorporating objective performance metrics, longitudinal modeling, and cross-context comparisons will be essential for advancing a more rigorous and globally relevant understanding of AI-supported learning in higher education.

5.4 Conclusion

This study examined the impact of ChatGPT usage on university students' academic performance, with particular attention to the mediating roles of self-efficacy and cognitive engagement (mental effort) and the moderating role of instructor support. While the findings confirm that generative AI can enhance students' learning outcomes by boosting self-efficacy and supporting cognitive engagement, its direct influence on academic performance is more nuanced. The evidence suggests that GenAI's effectiveness is contingent on how it is embedded within the broader learning design specifically, whether it is paired with supportive instructional strategies that scaffold student effort and encourage reflective use.

The results make three key contributions. First, they extend current debates on GenAI in higher education by shifting focus from simple adoption to pedagogical integration, showing that learning outcomes improve when GenAI tools are embedded within carefully structured tasks. Second, the study highlights the role of psychological mechanisms, demonstrating that self-efficacy, more than mental effort alone, drives the academic benefits of AI-enhanced learning. Third, it underscores the importance of instructor support as a critical condition for realizing the potential of GenAI in formal learning contexts.

For practice, these findings suggest that higher education institutions should not only provide access to AI tools but also design learning environments that foster self-efficacy, balance cognitive demands, and ensure active instructor presence. For research, future studies should adopt longitudinal and experimental designs to explore how sustained GenAI use deeper learning, critical thinking, and transferable skills.

In conclusion, generative AI such as ChatGPT has transformative potential for higher education, but its impact is maximized when aligned with intentional learning design and human-centered instructional practices.

Appendix 1

Full questionnaire items and measurement scales (1 = strongly disagree, 5= strongly agree)

Construct	Item No	Sample item	References	Response scale
ChatGPT usage	CU1	I use ChatGPT to clarify complex academic concepts	Çobanoğulları and Özbek [11]	1–5
	CU2	I use ChatGPT to assist with problem-solving tasks		1–5
	CU3	I use ChatGPT to support my learning for assignments or projects		1–5
	CU4	I frequently rely on ChatGPT to understand difficult topics		1–5
Cognitive engagement (mental effort)	ME1	Using ChatGPT requires me to think critically about the information provided	Paas [36]	1–5
	ME2	I actively invest mental effort to understand and integrate information when using ChatGP		1–5
	ME3	ChatGPT helps me focus my cognitive effort on understanding key concepts rather than searching for information		1–5
Academic self-efficacy Instructor support	SE1	I am confident I can use ChatGPT to successfully complete my assignments	van Zyl et al. [53]	1–5
	SE2	I believe I can achieve my learning goals with the support of ChatGPT		1–5
	SE3	Using ChatGPT enhances my belief in my academic abilities		1–5
	SE4	I can overcome learning challenges when using ChatGPT		1–5
	IS1	My instructors provide clear guidance on how to use ChatGPT effectively	Wang et al. [54]	1–5
	IS2	My instructors give feedback on how to use AI tools to improve learning outcomes		1–5
	IS3	Instructors encourage critical engagement with AI-generated content		1–5
	IS4	I receive sufficient support from instructors to integrate ChatGPT into my study tasks		1–5
Academic performance	AP1	Using ChatGPT has improved my academic performance	Cunningham [12]	1–5
	AP2	ChatGPT helps me achieve better grades		1–5
	AP3	Using ChatGPT enhances my learning effectiveness		1–5
	AP4	ChatGPT contributes to my understanding and mastery of course content		1–5
Learning outcomes	LO1	I have developed better problem-solving skills using ChatGPT	OECD [35]	1–5
	LO2	ChatGPT improves my ability to apply knowledge in practical tasks		1–5
	LO3	Using ChatGPT enhances my conceptual understanding of course material		1–5
	LO4	ChatGPT helps me retain information more effectively		1–5

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Author contributions
Abdulkadir Jeilani: Conceptualization, methodology, supervision, writing original draft, formal analysis. Mohamed Abdullahi: Data curation, formal analysis, writing review & editing. Mohamed Sahane: Investigation, validation, writing review & editing. Abdirahman Mohamed Dirie: Investigation, validation, writing review & editing.

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Data availability
The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
This study, titled *"Exploring the Impact of ChatGPT on Academic Performance: The Role of Cognitive Engagement, Self-Efficacy, and Instructor Support"*, was conducted in accordance with the principles of the Declaration of Helsinki. Ethical approval was obtained from the Institutional Review Board (MU-IRB) of Mogadishu University (Approval Number: MUIRB/13/25/001). All participants were informed about the study's purpose, procedures, potential risks, and benefits. Participation was voluntary, and participants (and their legal guardians, where applicable) provided written informed consent prior to involvement in the study. Participants were also informed of their right to withdraw at any time without consequence.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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