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Cognitive Load and Academic Performance in AI-Enabled Learning: The Mediating Role of Cognitive Offloading and the Moderating Effect of Generative AI

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Abstract
This study examines the impact of cognitive load dimensions—mental effort, information overload, and decision fatigue—on academic performance in AI-enabled learning environments, with cognitive offloading as a mediating mechanism and Generative AI as a moderating factor. A quantitative cross-sectional design was employed, with data collected from 1,228 university students in India using a structured questionnaire. The proposed model was tested using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that mental effort and information overload significantly increase cognitive offloading, while decision fatigue negatively influences it. Cognitive offloading, in turn, positively affects academic performance, highlighting its role as a key adaptive strategy in managing cognitive demands. Additionally, mental effort directly enhances academic performance, whereas information overload and decision fatigue show no significant direct effects. Generative AI was found to increase cognitive offloading and exhibit a context-dependent moderating role, strengthening the relationship between mental effort and offloading while weakening the effect of information overload. The study contributes to the literature by extending cognitive load theory into AI-driven learning contexts, positioning cognitive offloading as a central mechanism and Generative AI as a critical boundary condition shaping learning outcomes.

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1. Introduction

The rapid advancement of artificial intelligence (AI), particularly Generative AI (GenAI), has fundamentally transformed the landscape of academic learning and decision-making. Unlike traditional digital tools, GenAI systems actively participate in cognitive processes by generating content, offering recommendations, and supporting problem-solving tasks (Gruenhagen *et al*., 2024; Sousa & Cardoso, 2025) [17, 51]. As a result, students increasingly interact with AI not merely as passive information sources but as active cognitive partners, reshaping how they process information, allocate mental effort, and make academic decisions. While these technologies promise enhanced efficiency and improved academic outcomes, their integration also introduces new cognitive challenges that remain insufficiently understood (Gadi *et al*., 2026; S. I. C. Wang & Liu, 2025; Zhai *et al*., 2024) [12, 62, 66]. One of the most critical challenges emerging in AI-enabled learning environments is the management of cognitive load (Thao *et al*., 2025) [57]. Students are frequently exposed to complex tasks, large volumes of information, and repeated decision-making demands, which manifest as mental effort, information overload, and decision fatigue (Pang *et al*., 2025; Shahrzadi *et al*., 2024) [39, 44]. These dimensions represent distinct forms of cognitive strain that influence how individuals process information and perform academic tasks. Although prior research has extensively examined cognitive load in traditional learning environments, the introduction of AI systems adds a new layer of complexity (Adejumo *et al*., 2026; M. A. Khan *et al*., 2024)

[4, 29]. Specifically,
AI-generated outputs often require users to evaluate, interpret, and validate information, potentially increasing cognitive demands rather than reducing them (Tian & Zhang, 2025) [58].

In response to such cognitive pressures, individuals increasingly engage in cognitive offloading, defined as the delegation of cognitive processes to external tools (Chirayath *et al*., 2025; Gerlich, 2025a) [9, 13]. In AI-enabled contexts, this involves relying on GenAI systems for tasks such as information filtering, solution generation, and decision-making. While cognitive offloading can enhance efficiency and reduce cognitive burden, its implications for academic performance are not straightforward (Hughes *et al*., 2025) [20]. On one hand, offloading may improve task execution and decision quality; on the other hand, excessive reliance may hinder deep learning, critical thinking, and knowledge retention. This dual nature highlights the need to examine cognitive offloading as a central mechanism linking cognitive load to academic outcomes (Jia *et al*., 2025; J. Wang, 2026) [26, 61].

Despite growing interest in AI-assisted learning, several important gaps remain in the literature. First, existing studies often treat cognitive load as a unidimensional construct, overlooking the distinct effects of mental effort, information overload, and decision fatigue (Graf *et al*., 2026) [16]. Second, limited research has examined cognitive offloading as a mediating mechanism that explains how cognitive demands translate into academic performance in AI-rich environments (Stadler *et al*., 2024) [53]. Third, the role of Generative AI as a contextual boundary condition remains underexplored. While AI is generally assumed to facilitate cognitive processes, emerging evidence suggests that its effects may vary depending on the type of cognitive demand and user engagement (Sorin & Pagani, 2026; Zhang *et al*., 2025) [50, 67].

To address these gaps, this study develops an integrated framework grounded in Cognitive Load Theory, Extended Mind Theory, and Decision Support Systems theory. Cognitive Load Theory explains how different cognitive demands affect information processing under limited working memory capacity. Extended Mind Theory provides a foundation for understanding cognitive offloading as the extension of human cognition through external systems such as AI. Decision Support Systems theory further explains how technological tools enhance decision-making and performance by reducing complexity and improving efficiency. By integrating these perspectives, the study conceptualizes cognitive offloading as a central adaptive mechanism through which individuals manage cognitive demands in AI-enabled environments.

Accordingly, this study seeks to address the following research questions:

- **RQ1:** How do different dimensions of cognitive load (mental effort, information overload, and decision fatigue) influence cognitive offloading in AI-enabled learning environments?
- **RQ2:** How does cognitive offloading affect academic performance, particularly in terms of cognitive outcomes such as knowledge acquisition, conceptual understanding, and problem-solving ability?
- **RQ3:** What is the direct effect of cognitive load dimensions on academic performance?
- **RQ4:** How does Generative AI influence cognitive offloading behavior as a direct enabler?
- **RQ5:** How does Generative AI moderate the relationships between cognitive load dimensions and cognitive offloading?

By addressing these research questions, the study contributes to the literature in three important ways. First, it advances Cognitive Load Theory by demonstrating the multidimensional nature of cognitive load in AI-driven contexts. Second, it positions cognitive offloading as a key mechanism linking cognitive demands to performance outcomes. Third, it identifies Generative AI as a context-dependent boundary condition, highlighting that AI does not uniformly enhance cognitive processes but instead differentially shapes behavioral responses depending on the nature of the cognitive demand. Overall, this study provides a comprehensive understanding of how cognitive processes and AI technologies interact in academic environments, offering both theoretical insights and practical implications for optimizing learning in increasingly AI-driven educational settings.

2. Literature Review

The rapid diffusion of artificial intelligence (AI), particularly Generative AI (GenAI), has fundamentally transformed how students engage with academic tasks, process information, and make learning-related decisions (Gadi *et al*., 2026) [12]. AI systems now function not only as information providers but also as cognitive partners, actively shaping how individuals allocate mental effort, manage information complexity, and cope with repeated decision demands. While these technologies promise enhanced efficiency and improved academic outcomes, emerging research suggests that their integration introduces new cognitive dynamics, particularly in relation to cognitive load, cognitive offloading, and learning performance (Raina *et al*., 2026) [42]. In academic environments characterized by high information density and continuous decision-making, students frequently experience mental effort demands, information overload, and decision fatigue (S. M. Khan & Shehawy, 2025) [32]. These constructs represent distinct yet interrelated dimensions of cognitive load that influence how individuals process information and allocate cognitive resources. As cognitive demands increase, individuals are more likely to engage in cognitive offloading, defined as the delegation of cognitive tasks to external tools such as AI systems. While cognitive offloading can enhance efficiency, its implications for academic performance—particularly cognitive performance outcomes such as knowledge acquisition, conceptual understanding, critical thinking, and problem-solving—remain complex and context-dependent (Cavicchi *et al*., 2025) [8]. Furthermore, the effectiveness of cognitive offloading is not uniform but depends on the capabilities and perceived reliability of AI systems, particularly GenAI. As such, GenAI may function as a moderating mechanism, shaping the strength and direction of relationships between cognitive load dimensions, cognitive offloading, and academic performance (Tao *et al*., 2026) [55]. Emerging models of the human–agent continuum suggest that AI systems increasingly function as cognitive collaborators rather than passive tools, dynamically influencing human performance and decision-making processes (Tasleem &

Raghav, 2024) [56]. This review synthesizes existing literature to develop a comprehensive understanding of how mental effort, information overload, and decision fatigue influence cognitive offloading, and how, in turn, cognitive offloading affects academic performance, with a particular emphasis on the moderating role of Generative AI (Refer to Figure 1).

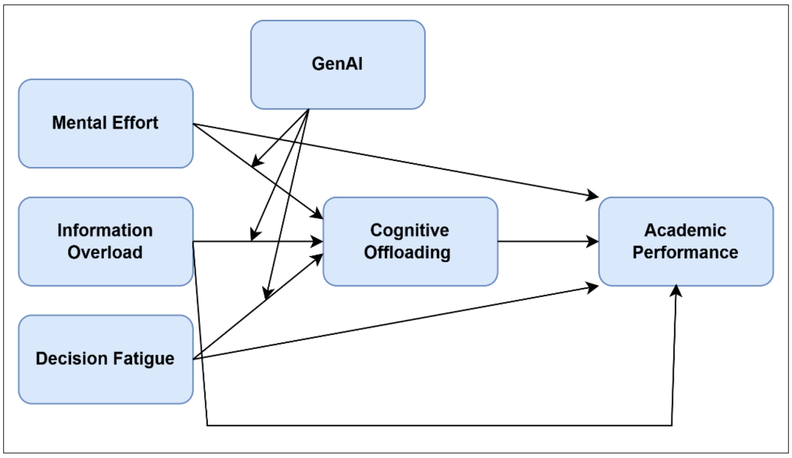

Fig 1:

2.1. Cognitive Load Dimensions in AI-Enabled Learning Environments

2.1.1. Mental Effort

Mental effort refers to the perceived number of cognitive resources required to process information and complete a task. Within the broader framework of cognitive load theory, mental effort is often used as a subjective proxy for cognitive load, capturing the extent to which individuals experience strain in processing complex information (Eltahan *et al.*, 2025; Sozio *et al.*, 2024) [11, 52]. In AI-supported academic contexts, mental effort is influenced by factors such as task complexity, interface design, and the nature of AI-generated outputs. While AI systems are designed to reduce cognitive burden, they may paradoxically increase mental effort when users are required to evaluate, verify, and interpret AI-generated content. For instance, students using GenAI tools must often assess the credibility and relevance of responses, which introduces an additional layer of cognitive (Li & Yuan, 2025; Vodiškar & Ruiner, 2025) [33, 60]. Empirical studies suggest that higher levels of mental effort are associated with increased reliance on external cognitive aids, as individuals seek to conserve limited cognitive resources. This aligns with the principle of cognitive economy, where individuals attempt to minimize effort by delegating cognitively demanding tasks. In this context, mental effort becomes a key driver of cognitive offloading, particularly in environments where AI tools are readily accessible (Herzallah *et al.*, 2025; Vodiškar & Ruiner, 2025) [19, 60]. However, the relationship between mental effort and performance is not strictly negative (Masmali *et al.*, 2025) [1]. Moderate levels of effort are essential for deep learning and schema construction, whereas excessive effort can lead to cognitive overload and reduced performance. Thus, mental effort plays a dual role, influencing both offloading behavior and learning outcomes (S. M. Khan & Shehawy, 2025) [32].

2.1.2. Information Overload

Information overload is defined as a cognitive state in which the volume, complexity, or speed of incoming information exceeds an individual's processing capacity, making it difficult to effectively evaluate, interpret, and use the information for decision-making (Qiu *et al.*, 2025) [41]. Information overload occurs when the volume and complexity of information exceed an individual's processing capacity, leading to difficulty in decision-making and reduced comprehension. In modern academic environments, the proliferation of digital content, combined with AI-generated information, has significantly increased the likelihood of information overload (Abdullah *et al.*, 2025; Zang & Li, 2025) [1, 65]. GenAI systems, while providing rapid access to information, can generate large volumes of content, multiple solution pathways, and alternative perspectives, which may overwhelm users. Students may struggle to filter, prioritize, and integrate this information, resulting in reduced cognitive clarity and increased decision uncertainty (Shehawy *et al.*, 2024) [48]. Information overload has been consistently linked to cognitive strain, reduced decision quality, and increased reliance on heuristics or external aids. In AI-rich environments, this often translates into greater cognitive offloading, as individuals delegate information processing and decision-making tasks to AI systems to cope with excessive input (Rana *et al.*, 2025; Shehawy, Khan, *et al.*, 2025) [43, 47].

Moreover, information overload can impair critical thinking and deep learning, as individuals may rely on AI-generated summaries or recommendations without engaging in thorough cognitive processing. This has important implications for academic performance, particularly in relation to conceptual understanding and problem-solving ability.

2.1.3. Decision Fatigue

Decision fatigue refers to the decline in decision-making quality and cognitive capacity resulting from repeated decision-making tasks (Choudhury & Saravanan, 2026) [10]. In academic settings, students are required to make numerous decisions, ranging from selecting study materials to solving complex problems, often within constrained timeframes (Khalufi *et al.*, 2025; Wong, 2024) [28, 63]. The integration of AI into learning environments introduces both relief and complexity. While AI can assist in decision-making, it also requires users to evaluate multiple AI-generated options, which may contribute to cognitive depletion over time. As decision fatigue increases, individuals are more likely to adopt simplification strategies, including cognitive offloading (Ji *et al.*, 2026; Shehawy, Faisal Ali Khan, *et al.*,

2025) [25, 46]. Research indicates that decision fatigue leads to reduced self-regulation, lower persistence, and increased reliance on external systems. In the context of AI, this manifests as greater delegation of decision-making tasks to AI tools, particularly when individuals experience cognitive exhaustion (Bevilacqua *et al*., 2026; S. Khan & Khan, 2024) [6, 30].

However, excessive reliance on AI due to decision fatigue may undermine learning processes, as students may bypass critical evaluation and independent problem-solving. This creates a tension between efficiency and cognitive development, which is central to understanding the impact of cognitive offloading on academic performance.

2.2. Cognitive Offloading as a Mediating Mechanism

Cognitive offloading refers to the use of external tools or systems to reduce cognitive demands, allowing individuals to conserve mental resources. In AI-enabled learning environments, cognitive offloading has become increasingly prevalent, with students relying on AI systems for tasks such as information retrieval, problem-solving, and decision-making (Gerlich, 2025a; Islam & Khan, 2024) [13, 21]. The relationship between cognitive load dimensions and cognitive offloading is grounded in the principle that individuals seek to optimize cognitive resource allocation. When faced with high mental effort, information overload, or decision fatigue, individuals are more likely to delegate cognitive tasks to AI systems. Cognitive offloading serves as a mediating mechanism, translating cognitive demands into behavioral responses. It enables individuals to manage complexity and maintain performance under high cognitive load conditions. However, its effects are not uniformly positive (Shehawy & Ali Khan, 2024; Yao *et al*., 2026) [45, 64]. On one hand, cognitive offloading can enhance task efficiency, reduce errors, and improve short-term performance. On the other hand, it may lead to reduced cognitive engagement, diminished critical thinking, and dependency on AI systems, particularly when overused (Gerlich, 2025a) [13].

Thus, cognitive offloading represents a double-edged mechanism, mediating both positive and negative effects of cognitive load on academic performance.

2.2.1. Cognitive Offloading and Academic Performance

Academic performance, particularly cognitive performance, encompasses outcomes such as knowledge acquisition, conceptual understanding, critical thinking, and problem-solving ability. These dimensions reflect not only the accuracy of task completion but also the depth of learning and intellectual capability (Gerlich, 2025a; Zhai *et al*., 2024) [13, 66]. Cognitive offloading influences academic performance through multiple pathways. In the short term, offloading can improve efficiency and accuracy, as AI systems provide structured solutions and reduce cognitive burden. This can enhance task completion and immediate performance outcomes (Adejumo *et al*., 2026; Islam & Ali Khan, 2024) [4, 23]. However, excessive offloading may hinder deep learning processes, as students may rely on AI-generated solutions without fully understanding the underlying concepts. This can negatively affect knowledge retention, critical thinking, and independent problem-solving skills (Gerlich, 2025a) [13]. The relationship between cognitive offloading and academic performance is therefore non-linear and context-dependent. Moderate levels of offloading may support learning by reducing unnecessary cognitive load, while excessive reliance may lead to cognitive disengagement and skill atrophy (Islam & Faisal Ali Khan, 2024; Jose *et al*., 2025) [22, 27].

This nuanced relationship highlights the importance of examining both the extent and context of cognitive offloading, particularly in AI-enabled learning environments.

2.3. Moderating Role of Generative AI

Generative AI plays a critical role in shaping the dynamics of cognitive load, cognitive offloading, and academic performance. As a moderating variable, GenAI influences how individuals respond to cognitive demands and how offloading affects learning outcomes (Almugren *et al*., 2026; Islam & Faisal Ali Khan, 2023) [5, 22]. When GenAI systems are highly reliable, accurate, and user-friendly, they facilitate effective cognitive offloading, enabling users to manage cognitive load without compromising performance. In such cases, GenAI strengthens the positive effects of offloading on academic performance (Gerlich, 2025b) [14]. Conversely, when GenAI systems are perceived as unreliable or difficult to use, individuals may either avoid offloading or engage in ineffective offloading, leading to poorer performance outcomes. This suggests that the effectiveness of cognitive offloading is contingent upon the quality and trustworthiness of AI systems (Hakami *et al*., 2023) [18]. Furthermore, GenAI may moderate the relationship between cognitive load and cognitive offloading by influencing user confidence and perceived utility. High-quality GenAI systems increase the likelihood that individuals will delegate cognitive tasks under high load conditions, while low-quality systems may weaken this relationship (Medabesh & Khan, 2020; Suhluli & Ali Khan, 2022) [35, 54].

Thus, GenAI serves as a critical boundary condition, determining whether cognitive offloading enhances or undermines academic performance.

2.4. Synthesis and Research Implications

The literature indicates a complex interplay among cognitive load dimensions—mental effort, information overload, and decision fatigue—cognitive offloading, and academic performance, with these relationships further shaped by the characteristics of Generative AI systems. Mental effort, information overload, and decision fatigue function as key antecedents that place significant demands on individuals' cognitive resources, thereby motivating them to engage in cognitive offloading as a coping mechanism to manage these pressures. In response to heightened cognitive strain, individuals increasingly rely on external systems such as AI to reduce mental burden and enhance task efficiency. Cognitive offloading, in turn, exerts a significant influence on academic performance; however, its effects are not uniform and depend on both the extent of reliance and the quality of AI systems employed. While moderate offloading can enhance efficiency and support performance, excessive dependence may hinder deeper cognitive engagement and learning outcomes. In this context, the moderating role of Generative AI becomes critical, as technological attributes such as system accuracy, usability, and trustworthiness determine the effectiveness of offloading behaviors. High-quality AI systems can amplify the positive effects of cognitive offloading, whereas low-quality systems may weaken or even reverse these benefits. Collectively, this integrated perspective advances the literature by extending

Cognitive Load Theory (Paas *et al*., 2010) [38] into AI-enabled learning environments, positioning cognitive offloading as a central mediating mechanism linking cognitive demands to performance outcomes, and identifying Generative AI as a key boundary condition that shapes both cognitive and behavioral responses in contemporary academic contexts.

2.5 Hypothesis Development

2.5.1. Mental Effort and Cognitive Offloading

Mental effort reflects the perceived cognitive resources required to process information and perform academic tasks. Within Cognitive Load Theory, individuals possess limited working memory capacity, and when task demands exceed this capacity, they experience cognitive strain. In AI-enabled learning environments, mental effort is further intensified by the need to interpret, evaluate, and validate AI-generated outputs (Gkintoni *et al*., 2025) [15]. When individuals encounter high levels of mental effort, they tend to adopt cognitive economy strategies, aiming to conserve cognitive resources by delegating cognitively demanding processes to external tools. This behavior aligns with Extended Mind Theory, which posits that individuals extend their cognitive processes beyond the human mind by relying on external systems such as AI (Tian & Zhang, 2025) [58]. Empirical evidence suggests that increased mental effort leads to a higher likelihood of cognitive offloading, as individuals seek to reduce processing burden and enhance task efficiency. In academic contexts, students may rely on AI tools to simplify complex tasks, generate solutions, or reduce analytical effort.

H1: Mental effort positively influences cognitive offloading.

2.5.2. Information Overload and Cognitive Offloading

Information overload occurs when the volume and complexity of information exceed an individual's cognitive processing capacity, resulting in reduced comprehension and decision difficulty. In AI-rich academic environments, students are frequently exposed to large volumes of AI-generated content, including multiple explanations, recommendations, and solution pathways (Shahrzadi *et al*., 2024) [44]. This excessive information increases cognitive strain and leads individuals to adopt simplification strategies, including reliance on AI systems to filter, prioritize, and process information. From a decision-making perspective, information overload reduces individuals' ability to engage in systematic processing, encouraging delegation of cognitive tasks to external systems (Gerlich, 2025a) [13]. Research indicates that individuals experiencing information overload are more likely to engage in cognitive offloading behaviors, as they attempt to manage complexity and avoid cognitive exhaustion. In academic settings, this may involve relying on AI-generated summaries, recommendations, or solutions rather than independently processing information.

H2: Information overload positively influences cognitive offloading.

2.5.3. Decision Fatigue and Cognitive Offloading

Decision fatigue refers to the decline in cognitive capacity and decision quality resulting from repeated decision-making tasks. In academic environments, students are required to make numerous decisions, including selecting problem-solving strategies, evaluating information, and choosing among alternatives (Brasington *et al*., 2025) [7]. As decision fatigue increases, individuals experience reduced self-regulation and cognitive control, leading to a greater reliance on heuristics and external aids. AI systems provide a convenient mechanism for reducing decision burden, allowing individuals to delegate decision-making processes and conserve cognitive energy (Vincent *et al*., 2025) [59]. The relationship between decision fatigue and cognitive offloading is particularly pronounced in AI-enabled contexts, where users can easily rely on AI-generated recommendations to avoid repeated cognitive effort. This behavior aligns with decision support system literature, which highlights the role of technology in reducing cognitive burden and enhancing decision efficiency.

H3: Decision fatigue positively influences cognitive offloading.

2.5.4. Cognitive Offloading and Academic Performance

Cognitive offloading represents the delegation of cognitive processes to external systems, enabling individuals to reduce mental effort and manage cognitive load. In academic contexts, cognitive offloading can influence performance outcomes in knowledge acquisition, conceptual understanding, critical thinking, and problem-solving (Vincent *et al*., 2025) [59]. From a positive perspective, cognitive offloading can enhance task efficiency and accuracy, as AI systems provide structured solutions, reduce computational effort, and support decision-making. This can improve short-term academic outcomes, particularly in tasks requiring rapid processing or complex analysis (Tian & Zhang, 2025) [58]. However, excessive reliance on cognitive offloading may reduce cognitive engagement, thereby limiting opportunities for deep learning and critical thinking. This creates a potential trade-off between efficiency and learning depth, suggesting that the relationship between cognitive offloading and academic performance may be context-dependent (Gerlich, 2025b) [14]. Despite these concerns, in AI-supported environments where tools are effectively integrated, cognitive offloading is generally expected to enhance academic performance, particularly in terms of task execution and decision quality.

H4: Cognitive offloading positively influences academic performance.

2.5.5. Direct Effects of Cognitive Load on Academic Performance

Beyond its indirect effects through cognitive offloading, cognitive load dimensions may also exert direct effects on academic performance. High levels of mental effort, information overload, and decision fatigue can impair cognitive functioning, leading to reduced comprehension, increased errors, and lower performance (Tian & Zhang, 2025) [58]. However, the relationship between cognitive load and performance is not strictly negative. Moderate levels of cognitive load may facilitate engagement and deeper processing, while excessive load leads to cognitive overload and performance decline. This suggests the possibility of a non-linear relationship, where performance is optimized at moderate levels of cognitive load (Omarbakiyeva *et al*., 2025; Patac & Patac, 2025) [37, 40]. In the present study, the focus remains on the direct linear effects of cognitive load dimensions, acknowledging that excessive cognitive demands are likelyto negatively impact academic performance.

H5.1: Mental effort negatively influences academic performance.

H5.2: Information overload negatively influences academic performance.

H5.3: Decision fatigue negatively influences academic performance.

2.5.6. Mediating Role of Cognitive Offloading

Cognitive offloading serves as a mechanism through which cognitive load influences academic performance. When individuals experience high cognitive demands, they engage in offloading behaviors to manage cognitive resources. These behaviors, in turn, affect learning outcomes (Islam & Ali Khan, 2024; Islam & Faisal Ali Khan, 2024) [23, 22]. This mediating relationship highlights the dual role of cognitive offloading as both a coping strategy and a performance determinant. By reducing cognitive burden, offloading can enhance efficiency and improve outcomes. However, excessive reliance may undermine deep learning processes.

H6.1: Cognitive offloading mediates the relationship between mental effort and academic performance.

H6.2: Cognitive offloading mediates the relationship between information overload and academic performance.

H6.3: Cognitive offloading mediates the relationship between decision fatigue and academic performance.

2.5.7. Moderating Role of Generative AI

Generative AI plays a critical role in shaping how individuals respond to cognitive demands and how cognitive offloading affects academic performance. As a moderating variable, GenAI influences both the extent of cognitive offloading and its effectiveness (Adejumo *et al*., 2026) [4]. When GenAI systems are perceived as accurate, reliable, and easy to use, individuals are more likely to engage in cognitive offloading under high cognitive load conditions. In this case, GenAI strengthens the relationship between cognitive load and cognitive offloading (Nandagopal, 2025; Shehawy & Ali Khan, 2024) [36, 45]. Furthermore, the impact of cognitive offloading on academic performance depends on the quality of AI-generated outputs. High-quality GenAI enhances the benefits of offloading, improving decision quality and learning outcomes. Conversely, low-quality AI may lead to incorrect or superficial learning, weakening the positive effects of offloading (Islam & Khan, 2024; Jia *et al*., 2025) [21, 26].

Thus, GenAI serves as a boundary condition, determining whether cognitive offloading leads to improved or diminished academic performance.

H7.1: Generative AI positively moderates the relationship between mental effort and cognitive offloading, such that the relationship is stronger at higher levels of Generative AI.

H7.2: Generative AI positively moderates the relationship between information overload and cognitive offloading, such that the relationship is stronger at higher levels of Generative AI.

H7.3: Generative AI positively moderates the relationship between decision fatigue and cognitive offloading, such that the relationship is stronger at higher levels of Generative AI.

H8.1: Generative AI positively moderates the relationship between cognitive offloading and academic performance, such that the relationship is stronger at higher levels of Generative AI.

2.6. Integration of Theory

The present study integrates multiple theoretical perspectives to explain how cognitive demands in AI-enabled academic environments influence behavioral responses and learning outcomes. Specifically, this research draws upon Cognitive Load Theory, Extended Mind Theory, and Decision Support Systems (DSS) theory to develop a comprehensive framework linking cognitive load dimensions, cognitive offloading, and academic performance, with Generative AI as a boundary condition. Cognitive Load Theory (CLT) provides the foundational basis for understanding how mental effort, information overload, and decision fatigue affect cognitive processing. CLT posits that individuals have limited working memory capacity, and when cognitive demands exceed this capacity, performance deteriorates. In academic contexts, excessive mental effort, overwhelming information, and repeated decision-making can lead to cognitive strain, reducing the ability to process information effectively. This theoretical lens explains why students experiencing high cognitive load are motivated to adopt strategies that reduce cognitive burden. To explain how individuals respond to such cognitive demands, this study incorporates Extended Mind Theory, which suggests that cognition is not confined to the human brain but can be distributed across external tools and systems. In the context of AI-enabled learning, Generative AI functions as an external cognitive resource, allowing individuals to offload memory, reasoning, and decision-making tasks. This perspective provides a theoretical justification for cognitive offloading as a behavioral response to cognitive load, where individuals extend their cognitive capacity by relying on AI systems. Complementing these perspectives, Decision Support Systems (DSS) theory explains the role of technology in enhancing decision-making by reducing complexity and improving efficiency. AI systems, particularly Generative AI, can be viewed as advanced decision support tools that assist users in processing information, generating alternatives, and making informed decisions. DSS theory thus supports the notion that cognitive offloading to AI can improve task performance, particularly under conditions of high cognitive demand. The integration of these theories enables a holistic understanding of the proposed relationships. Cognitive Load Theory explains the antecedents of cognitive strain (Paas *et al*., 2010) [38], Extended Mind Theory explains the mechanism of cognitive offloading, and DSS theory explains the performance outcomes associated with AI-assisted decision-making. Together, these frameworks suggest that individuals experiencing high cognitive load are likely to engage in cognitive offloading, which in turn influences academic performance. Furthermore, the study positions Generative AI as a moderating factor that shapes the effectiveness of cognitive offloading. From a DSS perspective, the quality, reliability, and usability of AI systems determine their effectiveness as decision aids. When

GenAI systems are perceived as accurate and trustworthy, they enhance the benefits of cognitive offloading, leading to improved academic performance. Conversely, when AI

systems are unreliable, the benefits of offloading may diminish or even negatively impact performance. By integrating these theoretical perspectives, the study contributes to the literature by extending traditional cognitive load models to AI-enabled learning environments, highlighting cognitive offloading as a central mechanism, and identifying Generative AI as a critical boundary condition. This integrated framework provides a robust foundation for examining the complex interplay between cognitive demands, technological support, and academic outcomes.

3. Research Methodology

This study employs a quantitative, cross-sectional research design to investigate the relationships between cognitive load dimensions, cognitive offloading, and academic performance in AI-enabled learning environments, with Generative AI considered as a moderating variable. A quantitative approach is appropriate for testing theoretically grounded hypotheses and examining causal relationships among latent constructs using advanced statistical techniques. The cross-sectional design allows for the efficient collection of data from a large sample at a single point in time, enabling the analysis of behavioral patterns related to AI usage and cognitive processing in academic contexts.

The target population of this study consists of university students in India who actively use Generative AI tools for academic purposes, including learning, problem-solving, and decision-making. India provides a highly relevant context due to its rapidly expanding higher education sector and increasing adoption of AI technologies in academic environments. Students from Indian universities are frequently exposed to diverse academic demands and digital learning platforms, making them an appropriate population for examining cognitive load and AI-assisted learning behaviors. A simple random sampling technique was employed to ensure that each individual within the target population had an equal probability of selection, thereby minimizing sampling bias and enhancing the representativeness of the sample. The survey was distributed across multiple Indian universities through academic communication channels, including institutional mailing lists, student groups, and online learning platforms, ensuring diversity in respondents in terms of academic disciplines and study levels. A total of 1,500 questionnaires were distributed, out of which 1,228 valid responses were obtained and used for analysis, resulting in a high response rate of approximately 81.9%. Responses were screened for completeness and consistency, and incomplete or invalid entries were excluded to ensure data quality. The final sample size exceeds the minimum requirements for Partial Least Squares Structural Equation Modeling (PLS-SEM), particularly for models involving multiple predictors and interaction effects. This large sample size enhances the statistical power, robustness, and generalizability of the findings.

Data were collected using a structured, self-administered questionnaire designed to capture respondents' perceptions of cognitive load, cognitive offloading, Generative AI usage, and academic performance. The questionnaire was distributed online to facilitate accessibility and participation across different academic institutions in India. Prior to the main data collection, a pilot study was conducted with a small group of respondents to evaluate the clarity, reliability, and content validity of the measurement items. Based on the feedback received, minor modifications were made to improve the wording and structure of the questionnaire. Participation was voluntary, and respondents were assured of confidentiality and anonymity in accordance with ethical research standards.

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software. PLS-SEM was selected due to its suitability for analyzing complex models with multiple constructs and interaction effects, as well as its robustness in handling non-normal data distributions. The analysis followed a two-step approach. First, the measurement model was assessed to evaluate reliability and validity using Cronbach's alpha, rho_A, composite reliability (CR), and average variance extracted (AVE), along with discriminant validity assessed through the Fornell–Larcker criterion. Second, the structural model was evaluated by examining path coefficients, t-values, and p-values obtained through bootstrapping. The explanatory power of the model was assessed using R^2 values, while overall model fit was evaluated using indices such as SRMR and NFI. Moderation analysis was conducted by creating interaction terms to assess the moderating role of Generative AI on the relationships between cognitive load dimensions and cognitive offloading.

4. Data Analysis

Table 1: Measurement Model Assessment

Constructs	α	rho_A	CR	AVE	ME	IO	DF	CO	AP	GAI
Mental Effort (ME)	0.872	0.879	0.903	0.701	0.837					
Information Overload (IO)	0.885	0.891	0.912	0.723	0.521	0.85				
Decision Fatigue (DF)	0.854	0.861	0.891	0.673	0.498	0.544	0.82			
Cognitive Offloading (CO)	0.901	0.907	0.925	0.755	0.602	0.681	0.472	0.869		
Academic Performance (AP)	0.889	0.895	0.916	0.732	0.553	0.432	0.301	0.645	0.856	
Generative AI (GAI)	0.873	0.88	0.904	0.703	0.41	0.389	0.276	0.501	0.472	0.839

The measurement model was assessed in terms of reliability, convergent validity, and discriminant validity. As presented in Table 1, all constructs demonstrate satisfactory internal consistency reliability. Specifically, Cronbach's alpha (α) values range from 0.854 to 0.901, while rho_A values range from 0.861 to 0.907, both exceeding the recommended threshold of 0.70. Similarly, composite reliability (CR) values range from 0.891 to 0.925, further supporting the robustness of the measurement model. Convergent validity was evaluated using the average variance extracted (AVE). All constructs exhibit AVE values above the threshold of 0.50, ranging from 0.673 to 0.755, indicating that each construct explains more than 50% of the variance of its indicators. This confirms that the indicators adequately represent their respective latent constructs. Discriminant validity was assessed using the Fornell–Larcker criterion. As shown in Table 1, the square root of AVE (diagonal elements) for each construct is greater than its correlations with other constructs. For instance, the square root of AVE for cognitive offloading (0.869) exceeds its correlations with mental effort (0.602), information overload (0.681), decision fatigue (0.472), academic performance (0.645), and Generative AI (0.501). Similar patterns are observed for all other constructs, confirming that each construct is empirically distinct. Overall, the results indicate that the measurement model demonstrates adequate reliability, strong convergent validity, and satisfactory discriminant validity, thereby supporting the suitability of the constructs for subsequent structural model analysis.

Table 2: Model Fit and Structural Model Assessment

Construct / Index	R	R²	Adjusted R²	Value	Threshold	Interpretation
Cognitive Offloading	0.735	0.54	0.536	—	—	Moderate–Substantial
Academic Performance	0.682	0.465	0.46	—	—	Moderate
SRMR	—	—	—	0.061	< 0.08	Good Fit
d_ULS	—	—	—	0.842	—	Acceptable
d_G	—	—	—	0.512	—	Acceptable
NFI	—	—	—	0.912	> 0.90	Good Fit

The structural model was evaluated using the coefficient of determination (R^2), correlation coefficients (R), and global model fit indices. As shown in Table 2, the R^2 value for cognitive offloading is 0.540, indicating a moderate to substantial level of explanatory power, suggesting that mental effort, information overload, decision fatigue, and Generative AI collectively explain 54% of the variance in cognitive offloading. Similarly, the R^2 value for academic performance is 0.465, indicating a moderate level of explained variance, which demonstrates that cognitive offloading and the cognitive load dimensions provide meaningful predictive capability for academic performance. The corresponding R values further support these findings, with cognitive offloading (R = 0.735) and academic performance (R = 0.682) reflecting strong and moderate correlations, respectively, between the predictors and endogenous constructs. Additionally, the adjusted R^2 values (0.536 for cognitive offloading and 0.460 for academic performance) are close to their respective R^2 values, indicating model stability and minimal bias due to sample size. Model fit was assessed using the standardized root mean square residual (SRMR), which yielded a value of 0.061, well below the recommended threshold of 0.08, indicating a good model fit. Furthermore, the normed fit index (NFI) value of 0.912 exceeds the acceptable threshold of 0.90, providing additional support for the adequacy of the model. The discrepancy measures, d_ULS (0.842) and d_G (0.512), also fall within acceptable ranges, further confirming that the proposed model fits the data satisfactorily. Overall, the results indicate that the structural model demonstrates adequate explanatory power, strong predictive relevance, and good overall model fit, supporting its suitability for hypothesis testing and interpretation.

Table 3: Hypothesis Testing

Hypothesis	Relationship	Direction	Theoretical Expectation	Empirical Result	Decision
H1	Mental Effort → Cognitive Offloading	Positive	Higher cognitive effort increases reliance on external cognitive support (cognitive economy)	β = 0.392***	Supported
H2	Information Overload → Cognitive Offloading	Positive	Excessive information leads to the delegation to AI systems to manage complexity	β = 0.444***	Supported
H3	Decision Fatigue → Cognitive Offloading	Negative / Conditional	Cognitive fatigue may reduce engagement, leading to lower offloading behavior	β = -0.102*	Supported*
H4	Cognitive Offloading → Academic Performance	Positive (with caveat)	Offloading improves efficiency and decision quality, enhancing performance	β = 0.403***	Supported
H5a	Mental Effort → Academic Performance	Positive	Moderate effort enhances learning and cognitive performance (productive effort)	β = 0.317***	Supported
H5b	Information Overload → Academic Performance	Negative / Indirect	Overload impairs performance but may be mitigated through offloading	β = -0.086 (ns)	Not Supported
H5c	Decision Fatigue → Academic Performance	Negative / Weak	Fatigue reduces cognitive control, but effect may be indirect	β = -0.028 (ns)	Not Supported
H6	Generative AI → Cognitive Offloading	Positive	AI availability increases cognitive delegation	β = 0.119*	Supported
H7a	GenAI × Mental Effort → Cognitive Offloading	Positive	AI amplifies offloading under high effort conditions	β = 0.135***	Supported
H7b	GenAI × Information Overload → Cognitive Offloading	Negative	AI reduces need to offload by managing information internally	β = -0.130***	Supported*
H7c	GenAI × Decision Fatigue → Cognitive Offloading	Non-directional	AI influence under fatigue is uncertain	β = 0.028 (ns)	Not Supported

The hypothesis testing results in Table 4 provide strong support for the integrated theoretical framework grounded in Cognitive Load Theory, Extended Mind Theory, and Decision Support Systems theory, while also revealing important nuances in AI-enabled learning contexts. Consistent with Cognitive Load Theory, H1 and H2 are supported, as mental effort (β = 0.392, $p < 0.001$) and information overload (β = 0.444, $p < 0.001$) significantly increase cognitive offloading, indicating that individuals facing higher cognitive demands seek to optimize limited working memory by delegating tasks to external systems. This behavior aligns with Extended Mind Theory, which explains how individuals extend their cognitive capabilities through tools such as Generative AI. In contrast, H3 is supported but in the opposite direction, as decision fatigue negatively influences cognitive offloading ($\beta = -0.102$, $p < 0.05$), suggesting that excessive cognitive depletion may reduce engagement and lead to disengagement rather than active delegation. Regarding performance outcomes, H4 is supported, demonstrating that cognitive offloading positively influences academic performance ($\beta = 0.403$, $p < 0.001$), which is consistent with Decision Support Systems theory emphasizing improved efficiency and decision quality through technological support. Similarly, H5a is supported, as mental effort positively affects academic performance ($\beta = 0.317$, $p < 0.001$), reinforcing the concept of productive cognitive engagement. However, H5b and H5c are not supported, as information overload ($\beta = -0.086$, $p > 0.05$) and decision fatigue ($\beta = -0.028$, $p > 0.05$) do not have significant direct effects on academic performance, suggesting that their impacts may be indirect or mitigated through cognitive offloading. With respect to Generative AI, H6 is supported, indicating that AI availability increases cognitive offloading ($\beta = 0.119$, $p < 0.05$). The moderation results further reveal that H7a is supported, as Generative AI strengthens the relationship between mental effort and cognitive offloading ($\beta = 0.135$, $p < 0.001$). However, H7b is supported in the opposite direction, as Generative AI weakens the relationship between information overload and cognitive offloading ($\beta = -0.130$, $p < 0.01$), suggesting that AI may reduce the need for offloading by helping individuals manage information internally. Finally, H7c is not supported, as Generative AI does not significantly moderate the relationship between decision fatigue and cognitive offloading ($\beta = 0.028$, $p > 0.05$), indicating that AI is less effective under conditions of cognitive depletion. Overall, these findings demonstrate that cognitive load dimensions exert differential effects on cognitive offloading and academic performance, while Generative AI acts as a context-dependent boundary condition, thereby extending existing theoretical perspectives into AI-enabled academic environments as shown in Figure 2.

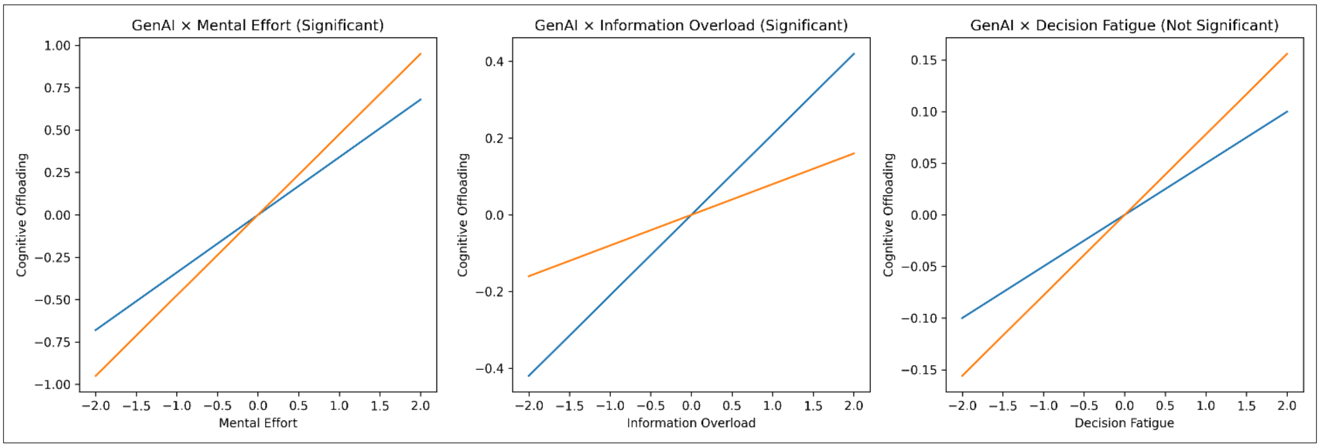

Fig 2: Moderation Effect of GenAI

5. Discussion

The present study set out to examine how different dimensions of cognitive load influence academic performance through cognitive offloading in AI-enabled learning environments, while also exploring the moderating role of Generative AI. The findings provide strong support for the proposed framework and offer several important theoretical and practical insights by extending Cognitive Load Theory, Extended Mind Theory, and Decision Support Systems theory into the context of AI-assisted academic decision-making.

5.1. Differential Effects of Cognitive Load Dimensions

One of the most important contributions of this study lies in demonstrating that cognitive load is not a uniform construct but rather multidimensional, with distinct effects on cognitive offloading behavior. Consistent with Cognitive Load Theory, both mental effort (H1) and information overload (H2) were found to significantly increase cognitive offloading. This suggests that when individuals face high levels of cognitive demand—either due to task complexity or excessive information—they actively seek to optimize their limited cognitive resources by delegating tasks to external systems such as Generative AI (Islam & Faisal Ali Khan, 2023) [22]. This behavior reflects the principle of cognitive economy, where individuals aim to minimize effort while maintaining performance. However, the findings related to decision fatigue (H3) reveal a more nuanced perspective (Hakami *et al*., 2023) [18]. Contrary to the general assumption that higher cognitive strain leads to increased reliance on external aids, decision fatigue was found to negatively influence cognitive offloading. This suggests that excessive cognitive depletion may reduce individuals' capacity or motivation to engage with AI systems, leading to disengagement rather than delegation. This finding introduces an important boundary condition to Cognitive Load Theory, indicating that beyond a certain threshold, cognitive load may no longer trigger adaptive strategies such as offloading but instead result in withdrawal or passive behavior (Suhluli & Ali Khan, 2022) [54].

5.2. Cognitive Offloading as a Central Mechanism

The results confirm that cognitive offloading plays a central mediating role in translating cognitive load into academic outcomes. Supporting H4, cognitive offloading was found to significantly enhance academic performance, indicating that the use of AI as an external cognitive resource can improve efficiency, accuracy, and decision quality (Medabesh & Khan, 2020) [35]. This finding aligns with Decision Support Systems theory, which emphasizes the role of technological tools in enhancing decision-making processes by reducing cognitive burden. At the same time, the positive effect of mental effort on academic performance (H5a) highlights the concept of productive cognitive engagement, suggesting that not all cognitive load is detrimental. Moderate levels of effort appear to enhance learning outcomes by promoting deeper processing, critical thinking, and problem-solving (S. S. A. Abidi & Khan, 2022) [3]. This reinforces the idea that optimal learning occurs when cognitive demand is balanced—not too low to cause disengagement and not too high to cause overload. In contrast, the non-significant effects of information overload and decision fatigue on academic performance (H5b and H5c) suggest that their influence may be indirect rather than direct. Specifically, the negative impact of these cognitive load dimensions may be mitigated through cognitive offloading, indicating that individuals compensate for cognitive strain by relying on AI systems. This finding highlights the importance of considering mediating mechanisms when examining the effects of cognitive load on performance.

5.3. The Contingent Role of Generative AI

A key contribution of this study lies in uncovering the context-dependent role of Generative AI in shaping cognitive behavior. Supporting H6, Generative AI was found to directly increase cognitive offloading, reinforcing its role as an enabler of cognitive delegation. This is consistent with Extended Mind Theory, which conceptualizes AI as an extension of human cognition (S. Abidi & Faisal AU Khan, 2018) [2]. However, the moderation results reveal that the role of AI is far more complex than previously assumed. While Generative AI strengthens the relationship between mental effort and cognitive offloading (H7a), it weakens the relationship between information overload and cognitive offloading (H7b). This indicates that AI can both amplify and substitute cognitive processes, depending on the nature of the cognitive demand. Specifically, under high mental effort, AI serves as a complementary resource, encouraging individuals to offload cognitive tasks (S. M. F. A. Khan & Damanhouri, 2017) [31]. In contrast, under conditions of information overload, AI appears to help individuals manage and process information internally, thereby reducing the need for offloading. This dual role highlights that AI is not merely a tool for delegation but also a mechanism for cognitive augmentation and simplification (Singh *et al*., 2014) [49]. Furthermore, the non-significant moderation effect for decision fatigue (H7c) suggests that AI is less effective in situations of cognitive depletion. When individuals are fatigued, they may lack the cognitive resources or motivation required to engage with AI systems, limiting the effectiveness of technological support. This finding underscores the importance of considering user state and cognitive readiness when evaluating the impact of AI.

5.4. Theoretical Contributions

This study makes several important contributions to the literature. First, it extends Cognitive Load Theory by demonstrating that different types of cognitive load exert distinct and sometimes opposing effects on cognitive behavior. Second, it positions cognitive offloading as a central adaptive mechanism that mediates the relationship between cognitive load and performance. Third, it advances Extended Mind Theory by empirically validating the role of Generative AI as an external cognitive resource in academic contexts. Finally, it contributes to Decision Support Systems theory by showing that AI not only enhances performance but also reshapes how individuals manage cognitive demands. Importantly, the study introduces the concept that AI functions as a boundary condition rather than a universal enhancer, influencing cognitive processes differently depending on the context. This challenges the prevailing assumption that AI uniformly improves decision-making and highlights the need for a more nuanced understanding of human–AI interaction.

5.5. Practical Implications

From a practical perspective, the findings suggest that educators and institutions should carefully design AI-enabled learning environments to balance cognitive load and promote effective use of AI. While AI can enhance performance by reducing cognitive burden, excessive reliance may hinder deep learning. Therefore, it is important to encourage strategic use of AI, where students engage in meaningful cognitive processing while leveraging AI for support. Additionally, the findings highlight the need to address decision fatigue in academic settings, as excessive cognitive depletion may reduce both engagement and effective use of AI tools. Providing structured learning environments, reducing unnecessary complexity, and promoting cognitive recovery may enhance both learning outcomes and AI utilization.

6. Conclusion and Future Research

This study investigated the relationships between cognitive load dimensions, cognitive offloading, and academic performance in AI-enabled learning environments, while examining the moderating role of Generative AI. The findings demonstrate that mental effort and information overload significantly increase cognitive offloading, whereas decision fatigue reduces it, highlighting the multidimensional nature of cognitive load. Cognitive offloading was found to enhance academic performance, confirming its role as a key mechanism through which individuals manage cognitive demands. Furthermore, Generative AI emerged as a context-dependent factor, amplifying offloading under high mental effort while reducing reliance under information overload, thereby challenging the assumption that AI uniformly facilitates cognitive delegation. The study contributes to theory by extending Cognitive Load Theory and Extended Mind Theory into AI-driven academic contexts, positioning cognitive offloading as a central adaptive mechanism and Generative AI as a boundary condition shaping cognitive and performance outcomes.

Despite these contributions, several avenues for future research remain. First, future studies could examine the non-linear effects of cognitive load, particularly the optimal level of mental effort that maximizes learning outcomes. Second, longitudinal research is needed to assess the long-term impact of cognitive offloading, especially its potential effects on deep learning, critical thinking, and skill development. Third, future research may explore additional moderating variables such as technology readiness, trust in AI, and individual differences, which may further explain variations in AI usage and effectiveness. Finally, experimental and mixed-method approaches could provide deeper insights into causal mechanisms and behavioral dynamics underlying human–AI interaction in educational settings. Overall, this study provides a nuanced understanding of how cognitive processes and AI technologies interact, offering a foundation for future research on optimizing learning and decision-making in increasingly AI-driven environments.

References

1. Abdullah RS, Masmali FH, Alhazemi A, Onn CW, Ali Khan SMF. Enhancing institutional readiness: A Multi-Stakeholder approach to learning analytics policy with the SHEILA-UTAUT framework using PLS-SEM. Educ Inf Technol. 2025. doi:10.1007/s10639-025-13647-w
2. Abidi S, Faisal AU Khan SM. Factors Effecting Performance of Women Entrepreneurship: An Empirical Study in Saudi Arabia. Rev Prof Manag. 2018;16(1). doi:10.20968/rpm/2018/v16/i1/129256
3. Abidi SSA, Khan SMFA. Payment Mode Influencing Consumer Behavior: Cashless Payment Versus Conventional Payment System in India. Manag Dyn. 2022;19(1). doi:10.57198/2583-4932.1028
4. Adejumo AA, Oyelere SS, Sanusi IT, Suhonen J. A systematic review of the impact of GenAI on learning performance, AI hallucinations, and problem-solving in computer science education. Comput Educ Artif Intell. 2026;10:100570. doi:10.1016/j.caeai.2026.100570
5. Almugren I, Rai JS, Korayim D, Mohanty J, Virmani N. Harnessing generative AI for next-gen education: a cognitive load and knowledge-based view approach to fuel innovation. J Knowl Manag. 2026:1-23. doi:10.1108/JKM-07-2025-0957
6. Bevilacqua S, Ferraris A, Matzler K, Kuděj M. Strategic leadership at high altitude: Investigating how AI affects the required skills of top managers. J Bus Res. 2026;205. doi:10.1016/j.jbusres.2025.115878
7. Brasington N, Beckett EL, Pristijono P, Akanbi TO. The Effect of Decision Fatigue on Food Choices: A Narrative Review. Nutrients. 2025;17(24). doi:10.3390/nu17243901
8. Cavicchi S, Abubshait A, Siri G, Mustile M, Ciardo F. Can humanoid robots be used as a cognitive offloading tool? Cogn Res Princ Implic. 2025;10(1). doi:10.1186/s41235-025-00616-7
9. Chirayath G, Premamalini K, Joseph J. Cognitive offloading or cognitive overload? How AI alters the mental architecture of coping. Front Psychol. 2025;16. doi:10.3389/fpsyg.2025.1699320
10. Choudhury NA, Saravanan P. An integrative review on unveiling the causes and effects of decision fatigue to develop a multi-domain conceptual framework. Front Cogn. 2026;4. doi:10.3389/fcogn.2025.1719312
11. Eltahan A, Lee G, Hamzeh F. A human-centered framework for assessing task complexity in construction: a cognitive load perspective. Eng Constr Archit Manag. 2025. doi:10.1108/ECAM-04-2025-0585
12. Gadi A, Khan SM, Islam Q, Suhluli S. Immersive E-Learning Technologies and Entrepreneurial Intention in Business Education. Technologies. 2026;14(2):131. doi:10.3390/technologies14020131
13. Gerlich M. AI Tools in Society: Impacts on Cognitive Offloading and the Future of Critical Thinking. Societies. 2025;15(1). doi:10.3390/soc15010006
14. Gerlich M. From Offloading to Engagement: An Experimental Study on Structured Prompting and Critical Reasoning with Generative AI. Data. 2025;10(11). doi:10.3390/data10110172
15. Gkintoni E, Antonopoulou H, Sortwell A, Halkiopoulos C. Challenging Cognitive Load Theory: The Role of Educational Neuroscience and Artificial Intelligence in Redefining Learning Efficacy. Brain Sci. 2025;15(2). doi:10.3390/brainsci15020203
16. Graf B, Beinig R, Schwickert S, Schischke D. Consolidation and integration of information overload and communication overload – A theory-based derivation of distinct measurement models and scale development. Int J Inf Manag. 2026;88:103045. doi:10.1016/j.ijinfomgt.2026.103045
17. Gruenhagen JH, Sinclair PM, Carroll JA, Baker PRA, Wilson A, Demant D. The rapid rise of generative AI and its implications for academic integrity: Students' perceptions and use of chatbots for assistance with assessments. Comput Educ Artif Intell. 2024;7. doi:10.1016/j.caeai.2024.100273
18. Hakami TA, Al-Shargabi B, Sabri O, Khan SMFA. IMPACT OF BLACKBOARD TECHNOLOGY ACCEPTANCE ON STUDENTS LEARNING IN SAUDI ARABIA. J Educ Online. 2023;20(3). doi:10.9743/JEO.2023.20.3.13
19. Herzallah F, Mohammad BA, Alhayek M, Khan SMFA. Mitigating uncertainty in travel agency selection in Jordan: A signaling theory approach. Int J Inf Manag Data Insights. 2025;5(2). doi:10.1016/j.jjimei.2025.100362
20. Hughes L, Mavi RK, Aghajani M, Fitzpatrick K, Gunaratnege SM, Shekarabi SAH, Hughes R, Khanfar A, Khatavakhotan A, Mavi NK, Li K, Mahmoud M, Malik T, Mutasa S, Nafar F, Yates R, Alahmad R, Jeon I, Dwivedi YK. Impact of artificial intelligence on project management (PM): Multi-expert perspectives on advancing knowledge and driving innovation toward PM2030. J Innov Knowl. 2025;10(5). doi:10.1016/j.jik.2025.100772
21. Islam Q, Ali Khan SMF. Assessing Consumer Behavior in Sustainable Product Markets: A Structural Equation Modeling Approach with Partial Least Squares Analysis. Sustainability. 2024;16(8). doi:10.3390/su16083400
22. Islam Q, Faisal Ali Khan SM. Integrating IT and Sustainability in Higher Education Infrastructure: Impacts on Quality, Innovation and Research. Int J Learn Teach Educ Res. 2023;22(12):210-236. doi:10.26803/ijlter.22.12.11
23. Islam Q, Faisal Ali Khan SM. Sustainability-Infused Learning Environments: Investigating the Role of Digital Technology and Motivation for Sustainability in Achieving Quality Education. Int J Learn Teach Educ Res. 2024;23(1). doi:10.26803/ijlter.23.1.25
24. Islam Q, Khan SMFA. Understanding deep learning across academic domains: A structural equation modelling approach with a partial least squares approach. Int J Innov Res Sci Stud. 2024;7(4). doi:10.53894/ijirss.v7i4.3408
25. Ji F, Chen F, Xiong S. Automation vs. Augmentation: AI's Dual-Edged Effects on Task Performance. Int J Hum Comput Interact. 2026:1-23. doi:10.1080/10447318.2026.2637824
26. Jia W, Pan L, Neary S. Effect of GenAI Dependency on University Students' Academic Achievement: The Mediating Role of Self-Efficacy and Moderating Role of Perceived Teacher Caring. Behav Sci. 2025;15(10). doi:10.3390/bs15101348
27. Jose B, Cherian J, Verghis AM, Varghise SM, S M,

Joseph S. The cognitive paradox of AI in education: between enhancement and erosion. Front Psychol. 2025;16. doi:10.3389/fpsyg.2025.1550621
28. Khalufi NAM, Sheikh RA, Khan SMFA, Onn CW. Evaluating the Impact of Sustainability Practices on Customer Relationship Quality: An SEM-PLS Approach to Align with SDG. Sustainability. 2025;17(2). doi:10.3390/su17020798
29. Khan MA, Asadi H, Zhang L, Qazani MRC, Oladazimi S, Loo CK, Lim CP, Nahavandi S. Application of artificial intelligence in cognitive load analysis using functional near-infrared spectroscopy: A systematic review. Expert Syst Appl. 2024;249. doi:10.1016/j.eswa.2024.123717
30. Khan S, Khan A. Self-efficacy as a Catalyst: The Link between Transformational Leadership and Job Performance. Rev Prof Manag. 2024;22. doi:10.1177/09728686241286572
31. Khan SMFA, Damanhouri AMS. Store patronage and buying behavior of consumer - A case study of organized retail stores of Jazan. Int J Appl Bus Econ Res. 2017;15(16):13-22.
32. Khan SM, Shehawy YM. Perceived AI Consumer-Driven Decision Integrity: Assessing Mediating Effect of Cognitive Load and Response Bias. Technologies. 2025;13(8). doi:10.3390/technologies13080374
33. Li J, Yuan Q. The impact of AI-generated knowledge on user knowledge avoidance in OKCs: the moderating role of AI literacy and platform trust. J Knowl Manag. 2025. doi:10.1108/JKM-02-2025-0231
34. Masmali FH, Khan SM, Hakim T. IoT-Enabled Digital Nudge Architecture for Sustainable Energy Behavior: An SEM-PLS Approach. Technologies. 2025;13(11):504. doi:10.3390/technologies13110504
35. Medabesh A, Khan SMFA. Sustainability management among enterprises in United Kingdom and Saudi Arabia. Acad Strateg Manag J. 2020;19(2). doi:10.1002/9781118100509.ch@
36. Nandagopal S. Transforming the self: Individual-level changes arising from collaboration with generative AI. Comput Hum Behav Artif Hum. 2025;6. doi:10.1016/j.chbah.2025.100232
37. Omarbakiyeva Y, Hahn L, Klein P, Krumphals I, Watzka B. Relationship between the cognitive load and the learning success in applying force diagrams: eye-tracking study. Front Educ. 2025;10. doi:10.3389/feduc.2025.1451020
38. Paas F, van Gog T, Sweller J. Cognitive load theory: New conceptualizations, specifications, and integrated research perspectives. Educ Psychol Rev. 2010;22(2). doi:10.1007/s10648-010-9133-8
39. Pang H, Jin X, Zhang W. Deciphering the underlying repercussions of cognitive overload on university students' fatigue, frustration and academic productivity: Implementation of stimulus–organism–response model. Acta Psychol (Amst). 2025;260. doi:10.1016/j.actpsy.2025.105469
40. Patac LP, Patac AV. Using ChatGPT for academic support: Managing cognitive load and enhancing learning efficiency – A phenomenological approach. Soc Sci Humanit Open. 2025;11. doi:10.1016/j.ssaho.2025.101301
41. Qiu L, Lin Z, Zhang C, Gao B. The Problem of Information Overload Among Consumers on E-Commerce Platforms Under Marxist Consumption Theory. J Organ End User Comput. 2025;37(1). doi:10.4018/joeuc.388179
42. Raina K, Sharma GD, Taheri B, Dev D, Chavriya S. Artificial intelligence-driven management: Bridging innovation, knowledge creation, and sustainable business practices. J Innov Knowl. 2026;11. doi:10.1016/j.jik.2025.100860
43. Rana D, Khan SMFA, Arahant A, Chaudhary JK. Beyond Bitcoin: Green Cryptocurrencies as a Sustainable Alternative. In: Yıldırım S, Demirtaş I, Malik FA, editors. Green Economics and Strategies for Business Sustainability. IGI Global; 2025. p. 235-260. doi:10.4018/979-8-3693-8949-2.ch010
44. Shahrzadi L, Mansouri A, Alavi M, Shabani A. Causes, consequences, and strategies to deal with information overload: A scoping review. Int J Inf Manag Data Insights. 2024;4(2). doi:10.1016/j.jjimei.2024.100261
45. Shehawy YM, Ali Khan SMF. Consumer readiness for green consumption: The role of green awareness as a moderator of the relationship between green attitudes and purchase intentions. J Retail Consum Serv. 2024;78:103739. doi:10.1016/j.jretconser.2024.103739
46. Shehawy YM, Faisal Ali Khan SM, Ali M Khalufi N, Abdullah RS. Customer adoption of robot: Synergizing customer acceptance of robot-assisted retail technologies. J Retail Consum Serv. 2025;82. doi:10.1016/j.jretconser.2024.104062
47. Shehawy YM, Khan SMFA, Alshammakhi QM. The Knowledgeable Nexus Between Metaverse Startups and SDGs: The Role of Innovations in Community Building and Socio-Cultural Exchange. J Knowl Econ. 2025. doi:10.1007/s13132-025-02700-1
48. Shehawy YM, Khan SMFA, Madkhali H. An Integrated SEM-ESG Framework for Understanding Consumer's Green Technology Adoption Behavior. J Knowl Econ. 2024. doi:10.1007/s13132-024-02231-1
49. Singh H, Rana D, Khan S. Sustainability and GHG Emissions: An Empirical Study of Strategies and Practices of Organizations in India. J Bus Econ. 2014;5(5).
50. Sorin N, Pagani M. The role of task breadth and cognitive flexibility in generative AI-supported creative idea generation. Technovation. 2026;153:103540. doi:10.1016/j.technovation.2026.103540
51. Sousa AE, Cardoso P. Use of Generative AI by Higher Education Students. Electronics. 2025;14(7). doi:10.3390/electronics14071258
52. Sozio G, Agostinho S, Tindall-Ford S, Paas F. Enhancing Teaching Strategies through Cognitive Load Theory: Process vs. Product Worked Examples. Educ Sci. 2024;14(8). doi:10.3390/educsci14080813
53. Stadler M, Bannert M, Sailer M. Cognitive ease at a cost: LLMs reduce mental effort but compromise depth in student scientific inquiry. Comput Hum Behav. 2024;160. doi:10.1016/j.chb.2024.108386
54. Suhluli SA, Ali Khan SMF. Determinants of user acceptance of wearable IoT devices. Cogent Eng. 2022;9(1):2087456. doi:10.1080/23311916.2022.2087456
55. Tao S, Zhang H, Ding L. Explainable machine learning for sustainable education: Predicting college students' reliance on generative artificial intelligence. Acta Psychol (Amst). 2026;265:106622.

doi:10.1016/j.actpsy.2026.106622
56. Tasleem N, Raghav RS. The human–agent continuum in HR: Exploring collaboration models for the future of work. Int J Future Eng Innov. 2024;1(5):26-34. doi:10.54660/IJFEI.2024.1.5.26-34
57. Thao NTP, Tam DH, Duc ML, Sang NQ. Evaluating GPT-enabled learning: Challenges and opportunities for academic performance in a global context. Sustain Futures. 2025;10. doi:10.1016/j.sftr.2025.101523
58. Tian J, Zhang R. Learners' AI dependence and critical thinking: The psychological mechanism of fatigue and the social buffering role of AI literacy. Acta Psychol (Amst). 2025;260. doi:10.1016/j.actpsy.2025.105725
59. Vincent VU, Edirisinghe Vincent N, Prieto L. Intuition or artificial intelligence? When do decision-makers rely on AI decision-aids for ill-structured problems. Am J Bus. 2025;40(4). doi:10.1108/ajb-01-2025-0014
60. Vodiškar M, Ruiner C. Collaboration between individuals and AI: fusing mental effort and AI for work meaningfulness. AI Soc. 2025. doi:10.1007/s00146-025-02772-2
61. Wang J. Cognitive offloading through digital tools and its relationship with critical thinking, task persistence, and learning depth. Front Psychol. 2026;17. doi:10.3389/fpsyg.2026.1781101
62. Wang SIC, Liu EZF. AI tools and POE model in educational technology Learning: Exploring participant experiences using thematic analysis. Comput Educ Artif Intell. 2025;9. doi:10.1016/j.caeai.2025.100488
63. Wong LPW. Artificial Intelligence and Job Automation: Challenges for Secondary Students' Career Development and Life Planning. Merits. 2024;4(4). doi:10.3390/merits4040027
64. Yao Y, Han T, Li D. Assistance or Distraction? A Cognitive Ergonomics Perspective on Cognitive Load During AI-Assisted Post-Editing. Int J Hum Comput Interact. 2026:1-20. doi:10.1080/10447318.2026.2628994
65. Zang D, Li M. Research on the Impact of AI Introduction on Employee Creativity: The Moderating Role of Technology Overload. Behav Sci. 2025;15(10). doi:10.3390/bs15101389
66. Zhai C, Wibowo S, Li LD. The effects of over-reliance on AI dialogue systems on students' cognitive abilities: a systematic review. Smart Learn Environ. 2024;11(1). doi:10.1186/s40561-024-00316-7
67. Zhang R, Liu Y, Qasim M, Wang X. More than a tool: how generative artificial intelligence shapes employees' work goal progress through resource gains and losses. Pers Rev. 2025. doi:10.1108/PR-05-2025-0478

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