

# Beyond Efficiency: Critical Thinking, Trust, and Learning Outcomes in Human-GenAI Partnerships within UAE Higher Education

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## Article

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# Abstract

GenAI is increasingly changing how students interact with academic tasks in higher education. This study explores the cognitive and behavioral pathways linking the intensity of AI use to student learning among undergraduate business students in the UAE. Drawing on Cognitive Load Theory and Social Cognitive Theory, the research employs a two-stage analytical approach that combines descriptive analysis with PLS-SEM, using cross-sectional census survey data from 91 students. The findings suggest that while higher AI usage enhanced student engagement, productivity, creativity, and trust in AI-generated outputs, the strongest predictor of learning outcomes, critical thinking, is not significantly enhanced by AI engagement. The study also identifies a behavioral procrastination effect associated with the availability of GenAI. Overall, it contributes to the growing body of literature on effective human-AI interaction in higher education, highlighting a disconnect between efficiency and learning.

## 1. Introduction

The rapid proliferation of Generative Artificial Intelligence (GenAI) tools has fundamentally altered the landscape of higher education. Since the release of ChatGPT in late 2022, the adoption of large language models (LLMs) in the academic world has followed one of the fastest technology diffusion trajectories ever recorded, with over 80 percent of students at selective elite institutions using GenAI for academic purposes by 2025 from less than 10 percent before Spring 2023 (Contractor & Reyes, 2025). Tools such as ChatGPT, Gemini, and Microsoft Copilot have transitioned from novelty to embedded workflow components, reshaping how undergraduate students conduct research, generate ideas, draft content, and manage their academic workload (Abbas et al., 2024; Meyer et al., 2023). The UAE is a particularly important context for examining AI-enabled learning due to its highly internationalized higher education ecosystem, rapid digital transformation agenda, and strong institutional emphasis on integrating artificial intelligence. While GenAI adoption among university students in the region has accelerated considerably, empirical evidence from the GCC and the UAE higher education sector remains comparatively limited, creating an important contextual and geographical gap in the emerging GenAI in higher education literature (Alsharefeen & Al Sayari, 2025; Tbaishat et al., 2025)

Further, despite this scale of adoption, a fundamental empirical question remains unresolved: whether GenAI tools are a genuine co-partner in student learning, augmenting cognitive capacity, deepening academic engagement, and improving learning outcomes, or do they primarily serve as an efficiency substitute that delivers productivity gains at the cost of deeper cognitive development? Although the emerging literature on GenAI in higher education increasingly documents outcomes such as improved efficiency, engagement, creativity, and learning support, the underlying mechanisms through which GenAI usage translates into meaningful learning outcomes remain insufficiently theorized and empirically examined. Existing studies predominately focus on adoption patterns, perceived usefulness, or direct outcome effects, often operationalizing GenAI usage as a generalized or binary phenomenon rather than examining how varying levels of GenAI engagement activate interconnected cognitive and

behavioral processes that shape learning experiences and academic performance (Chan & Hu, 2023; Bai & Wang, 2025; Wang et al., 2025)

The present study addresses this gap through a census survey conducted within a structured Gen AI – permitted instructional setting conducted at a US higher institution in Dubai during the academic year 2025–2026. The undergraduate business students enrolled in Finance, Global Business Management, and Marketing courses were explicitly permitted to use GenAI tools across a range of academic tasks, including take-home assessments, project-based submissions, individual and group presentations, and study preparation. This created a structured experiment setting in which pathways between GenAI usage and learning outcomes were directly observed and modeled across the entire student population. The study draws on a census population of 91 students and employs a two-stage analytical framework using Partial Least Squares- Structural Equation Modeling (PLS-SEM) to examine how GenAI usage intensity influences learning outcomes through interconnected cognitive and behavioral mechanisms, including engagement, productivity, creativity, critical thinking, and trust in GenAI outputs.

The results from the proposed model reflect an important theoretical distinction that extends beyond the dominant adoption-focused perspective in the existing GenAI literature. Rather than assuming that GenAI usage directly improves learning outcomes, the present study conceptualizes GenAI-enabled learning as a multi-stage process in which the intensity of GenAI use first stimulates student engagement with GenAI tools across activities such as research, idea generation, content development, and academic problem-solving. It is the depth and quality of this engagement that subsequently influence key cognitive and behavioral outcomes, including productivity, creativity, and critical thinking, which collectively shape students' perceived learning outcomes. In parallel, trust in GenAI operates as a distinct evaluative pathway through which repeated exposure to GenAI-generated outputs influences students' confidence in the reliability and usefulness of GenAI-assisted learning. Together, these interconnected pathways provide a more comprehensive explanation of GenAI-enabled learning.

The study contributes to the emerging literature on GenAI in higher education in four important ways. First, it operationalizes GenAI usage intensity as a formative construct that incorporates both the frequency and depth of GenAI engagement, thereby enabling a more nuanced understanding of how varying levels of GenAI interaction activate downstream learning processes. Second, the study develops and empirically tests a sequential engagement-mediated structural model within the UAE higher education context using PLS-SEM, linking GenAI usage intensity to learning outcomes through engagement, productivity, creativity, and critical thinking within a unified analytical framework. Third, the study identifies and quantifies a behavioral procrastination effect associated with the availability of GenAI, whereby students delayed task initiation despite reporting greater efficiency, highlighting an important behavioral trade-off in GenAI-assisted learning environments. Fourth, the findings reveal a significant paradox between students' strong verification behavior and comparatively weak formal attribution practices, with a large proportion of students cross-checking GenAI-generated information while sustainably fewer formally acknowledging AI usage in academic work. This contributes to the

growing discussion surrounding, academic integrity, responsible AI usage, and “AI-garism” in higher education (Chan, 2024; Lund et al., 2025)

The remaining paper proceeds as follows: Section 2 presents the theoretical framework and empirical literature, Section 3 describes the research design, survey instrument and analytical approach, and Section 4 presents the descriptive findings and results of the structural model assessment. Further, section 5 discusses the results and provides theoretical and practical implications, section 6 summarizes the study, acknowledges the limitations, and identifies directions for future research.

## **2. Literature Review and Theoretical Framework**

### **2.1 Theoretical Framework**

#### **2.1.1 An Integrated Framework for GenAI-Enabled Learning**

The present study adopts a technology-mediated learning perspective (Alavi & Leidner, 2001), which provides an overarching lens for understanding how digital technologies influence learning processes by shaping students' interactions with information and educational environments. Within the Gen AI context, this perspective recognizes that AI tools operate as interactive learning partners that influence student engagement, problem-solving processes, and learning experiences (Chan & Hu, 2023; Wang et al., 2025). This lens is particularly relevant for understanding how varying levels of AI usage intensity shape academic behaviors and perceived learning outcomes in the AI-enabled educational landscape.

To explain the cognitive and behavioral mechanisms underlying GenAI-enabled learning, the study selectively integrates two complementary theoretical perspectives. Cognitive Load Theory (CLT; Sweller, 1988) explains how AI tools may reduce the cognitive burden of information processing and task execution, potentially allowing students to allocate more cognitive effort to higher-order processes such as creativity, analytical reasoning, and critical thinking. Social Cognitive Theory (SCT; Bandura, 1986) supports examining behavioral engagement and trust dynamics by emphasizing that repeated interactions with technology shape users' beliefs, self-efficacy, and behavioral patterns.

In the GenAI context, this perspective helps explain how continued exposure to GenAI outputs may influence students' confidence and willingness to rely on such tools for academic tasks (Wang & Chuang, 2024). Self-Determination Theory (SDT; Ryan & Deci, 2000) further complements this framework by suggesting that students are more likely to engage deeply with GenAI tools when such interactions enhance perceived competence and support autonomous learning behaviors. In GenAI-enabled learning environments, students who perceive greater control, efficiency, and capability when interacting with GenAI tools may demonstrate higher-quality engagement and more exploratory usage patterns. Within the present study, SDT therefore provides a limited but relevant motivational lens for understanding variations in engagement depth and AI-assisted learning behavior.

## 2.1.2 Behavioral and Evaluative Mechanisms: Social Cognitive Perspective

SCT explains how repeated GenAI interactions shape students' confidence in AI accuracy through experiential learning. Each successful interaction provides evidence about AI reliability, potentially calibrating trust upward through accumulated experience. This positions the intensity of AI use as a potential antecedent of trust, independent of engagement depth.

SCT's self-efficacy construct, which reflects an individual's belief in their capacity to perform specific behaviors, helps explain variation in the quality of engagement. Wang and Chuang (2024) operationalize this as AI self-efficacy in the Gen AI context, with confidence in one's ability to interact productively with AI tools. Research shows that students with higher AI self-efficacy tend to engage more exploratively with AI outputs, generate more divergent ideas, and refine their responses iteratively, which may contribute to stronger creative outcomes (Habib et al., 2023). This suggests that creative outcomes may depend on the quality of engagement, not merely on usage frequency.

CLT complements this behavioral perspective by explaining how GenAI tools may reduce extraneous cognitive load by reducing mental effort devoted to task-irrelevant processing, thereby freeing working memory resources for germane processing (Sweller, 1988; Jose et al., 2025). Further, Martin et al. (2025) stress that structured GenAI integration can reduce cognitive load and redirect resources toward deeper processing. However, the same mechanism that produces efficiency gains also creates the potential for cognitive offloading, in which students may passively accept outputs without evaluation. Emerging educational technology scholarship has increasingly emphasized that while GenAI tools can support personalized learning, idea generation, and rapid access to information, they may also reshape students' cognitive engagement patterns by altering how learners process, verify, and reflect on academic content (Kasneji et al., 2023). CLT, therefore, suggests that critical thinking outcomes are likely contingent on the quality of engagement with AI outputs.

## 2.2 Empirical Studies

GenAI adoption in higher education has accelerated dramatically across diverse educational contexts. Large-scale evidence indicates that over 80% of students at an elite US university and more than 60% of 72,615 Chinese undergraduate students used GenAI for academic purposes during 2023–2025 (Contractor & Reyes, 2025; Guo et al., 2025). Similarly, studies from the UAE report strong perceived benefits and high AI self-efficacy among students (Tbaishat & Elfadel, 2025), although empirical research examining the cognitive and behavioral mechanisms linking GenAI use to learning outcomes remains limited.

The empirical literature consistently shows that high-performing GenAI users are distinguished not by usage frequency alone but by the quality of interaction. Deep, iterative engagement characterized by dialogue, refinement, and knowledge co-construction predicts stronger engagement outcomes (Peng et al., 2025), consistent with Xia et al.'s (2025) meta-analysis, which shows positive effects across

cognitive, behavioral, emotional, and agentic engagement. Students primarily use GenAI for idea generation and research, positioning it as a brainstorming and exploratory co-partner rather than an answer-generation tool (Chan & Hu, 2023). Moreover, well-designed iterative prompting has emerged as an important AI literacy skill that enhances the quality of human–AI interaction (Lee & Palmer, 2025).

Active engagement with GenAI has been consistently associated with improvements in productivity and efficiency. A systematic review of 158 studies reported significant gains in writing efficiency and task completion speed (Daniel et al., 2025), while longitudinal evidence found improved task completion and time savings alongside reduced independent effort among some students (Abbas et al., 2024). Similarly, Bastani et al. (2024) showed that students who relied on AI without actively processing its outputs performed 17% worse on subsequent assessments, suggesting that efficiency gains may come at the expense of deeper learning when AI substitutes rather than supports cognitive effort.

Critical thinking presents a particularly complex empirical picture. Habib et al. (2023) found that AI-assisted exploration of alternative approaches enhanced divergent thinking, particularly when students engaged in exploratory hypothesis testing, iterative idea refinement, and the generation of multiple perspectives. In contrast, Gerlich (2025) reported that instrumental, non-exploratory use of GenAI constrained students' ability to generate independent ideas. Similarly, Suriano et al. (2025) demonstrated that iterative interactions with ChatGPT involving active re-prompting, output evaluation, and synthesis with prior knowledge significantly strengthened critical thinking skills. Consistent with Cognitive Load Theory, these findings suggest that critical thinking develops when students critically evaluate and integrate AI-generated content rather than passively accepting it. However, research indicates that such gains depend on students adopting an evaluative rather than an acceptance-oriented approach to AI outputs, a distinction closely related to verification behavior (Melisa et al., 2025; Sánchez et al., 2025). Most existing studies treat critical thinking as a direct outcome of AI use rather than examining how verification behavior shapes the relationship between engagement and critical thinking development.

Concurrent with GenAI engagement, trust in GenAI operates through a distinct affective-evaluative pathway. Wang et al. (2025) found that trust serves as the primary affective mediator between usage experience and sustained learning engagement. Low levels of trust may result in skepticism and avoidance despite institutional support for GenAI adoption. Research further indicates that both performance expectancy and facilitating conditions strengthen trust in GenAI in both system-like and human-like forms, with human-like trust being particularly important for students' continued engagement in GenAI-assisted learning.

Productivity, creativity, critical thinking, and trust contribute to learning outcomes through distinct yet interconnected pathways. A meta-analysis of 68 experimental studies reported a moderate but statistically significant positive effect of GenAI-supported interventions on learning outcomes, primarily through personalized feedback and adaptive engagement (Bai & Wang, 2025). Likewise, Liang et al. (2023) found that learning motivation, creative self-efficacy, and confidence mediate the relationship

between GenAI output quality and academic achievement, supporting the multi-pathway structure proposed in the present study.

Academic integrity remains a central concern in GenAI-enabled learning. Chan (2024) introduced the term "AI-giarism" to describe the submission of AI-generated work without appropriate attribution, while Lund et al. (2025) found that students' ethical beliefs, rather than institutional policies, primarily shape perceptions and behaviors related to academic misconduct. Within the GCC, inconsistent institutional guidance further complicates students' navigation of trust, responsible AI use, and attribution practices (Alsharefeen & Al Sayari, 2025), reinforcing the importance of examining these issues in the UAE higher education context.

## 2.3 Research Gap

This study is motivated by three interconnected gaps. First, existing research primarily focuses on adoption decisions or on direct relationships between usage and outcomes, leaving the cognitive and behavioral mechanisms linking usage to outcomes unexplored. Many studies treat GenAI use as a binary concept rather than as a continuous construct with varying levels of intensity. While there is evidence of a relationship between GenAI usage and learning outcomes, there is limited understanding of how different levels of GenAI engagement influence these outcomes. This study explicitly models pathways of sequential engagement and trust, offering mechanistic explanations rather than merely descriptive accounts.

Second, research on the UAE and the broader Gulf region is significantly underrepresented. Alsharefeen & Al Sayari (2025) pointed out the Gulf Cooperation Council (GCC) as a critical research gap. Notably, existing studies in the UAE often rely on perceptual surveys rather than on structured interventions that include behavioral and learning outcome data (Tbaishat et al., 2025). Thus, this study aims to contribute population-level, intervention-based empirical data from an international university in the UAE.

Third, two behavioral phenomena remain empirically unexamined in structured interventions within this context. The first is the procrastination effect caused by the availability of AI (Lahmer, 2025), and the second is the verification-attribution paradox (Chan, 2024). This study aims to provide an empirical examination of both phenomena within the realm of business education in the UAE.

## 2.4 Conceptual Model and Hypotheses Development

Drawing on the integrated framework and the empirical literature provided in the previous section, this study proposes a structural model that examines two distinct pathways linking GenAI usage to learning outcomes (see Fig. 1). The first pathway is sequential and engagement-mediated, GenAI usage intensity is proposed to positively influence student engagement with AI tools in academic tasks (H1), which in turn is expected to contribute to three parallel cognitive and behavioral outcomes, with productivity (H2), creativity (H3), and critical thinking (H4), each of which may independently contribute to perceived learning outcomes (H6, H7, H8 respectively).

The second pathway operates as a direct affective-evaluative mechanism. GenAI usage intensity is proposed to shape trust in GenAI (H5) through accumulated perceptions of reliability developed across repeated interactions. Trust in GenAI, in turn, is expected to positively influence perceived learning outcomes (H9) through increased confidence in the reliability and usefulness of AI-generated outputs. This two-pathway architecture accounts for both deep cognitive engagement and confidence effects within a coherent structural framework. Overall, the nine hypotheses are summarized in Table 1, and Fig. 1 presents the conceptual framework with theoretical anchors mapped to construct blocks.

| Table 1<br>Study Hypotheses and Theoretical Grounding |                                       |                                          |
|-------------------------------------------------------|---------------------------------------|------------------------------------------|
| Hypothesis                                            | Relationship                          | Theoretical Grounding                    |
| H1                                                    | AI Usage Intensity → AI Engagement    | Technology-mediated learning perspective |
| H2                                                    | AI Engagement → Productivity          | Cognitive Load Theory                    |
| H3                                                    | AI Engagement → Creativity            | Cognitive Load Theory                    |
| H4                                                    | AI Engagement → Critical Thinking     | Cognitive Load Theory                    |
| H5                                                    | AI Usage Intensity → Trust in AI      | Social Cognitive Theory                  |
| H6                                                    | Productivity → Learning Outcomes      | Technology-mediated learning perspective |
| H7                                                    | Creativity → Learning Outcomes        | Technology-mediated learning perspective |
| H8                                                    | Critical Thinking → Learning Outcomes | Cognitive Load Theory                    |
| H9                                                    | Trust in AI → Learning Outcomes       | Social Cognitive Theory                  |
| Source: Author's Own Contribution                     |                                       |                                          |

Figure 1: Conceptual Framework

Source: Author's Own Contribution

### 3. Research Design and Methodology

#### 3.1 Research Design

The present study adopts a quantitative, explanatory research design to investigate the role of GenAI as a co-partner in undergraduate student learning. The study employs a cross-sectional survey design situated within a GenAI-permitted instructional context and is grounded in theory-driven hypothesis testing, aiming to examine how GenAI usage translates into learning outcomes through multiple cognitive and behavioral mechanisms. Specifically, the research seeks to understand the pathways

through which GenAI usage intensity influences engagement, productivity, creativity, critical thinking, and trust, and how these factors collectively shape perceived learning outcomes.

## **3.2 Study Context and Participant Pool**

The study is situated in a GenAI-permitted instructional context implemented during the Fall 2025 academic term (August – December 2025) involving undergraduate business students enrolled in BS Finance, BS Global Business Management, and BS Marketing courses. Following the completion of the experiment, the survey data were collected from the students during the subsequent Spring 2026 period. These students were explicitly permitted to use GenAI tools, such as ChatGPT, Gemini, Microsoft Copilot, and others, while completing their core academic tasks, including graded take-home assessments, project-based written submissions, individual and group presentations, and study material preparation. Clear ethical boundaries and expectations regarding academic integrity were communicated to the students. They were permitted to use the AI tools for idea generation, content structuring, conceptual clarification, drafting, and refinement. Their assessments emphasized analytical judgment and the originality of their final submissions.

Within this instructional intervention, the initial participant pool comprised 100 students enrolled in three finance courses, 51 in two marketing courses, and 90 in management courses. Although the intention was to capture a broad cross-section of business students, we discovered significant overlap among students across courses and specializations within the business department during implementation. Many students were concurrently enrolled in Finance, Marketing, and management courses while participating in the GenAI-enabled instructional assessments. As a result, the study ultimately converged into a single census study, representing a full population of 91 students.

## **3.3 Designing the Survey Instrument and Validation**

The survey instrument was designed to capture the multidimensional nature of GenAI-enabled learning, incorporating constructs such as GenAI usage intensity, engagement, productivity, creativity, critical thinking, trust, and learning outcomes. The development of the instrument was grounded in established measurement practices in educational technology and behavioral research (Davis, 1989; Venkatesh et al., 2003; Teo, 2011). Perceptual constructs were measured using five-point Likert-type scales, while behavioral dimensions such as usage frequency, engagement patterns, and time savings were captured using ordinal and frequency-based measures. This combination of measurement approaches enabled the study to capture both subjective perceptions and actual usage behaviors, thereby enhancing construct representation (Podsakoff et al., 2003).

To ensure validity and clarity, a pilot study was conducted with 15 undergraduate students, comprising 5 students each from the Finance, Marketing, and Global Business Management programs, prior to the full-scale deployment of the survey. The pilot aimed to assess the clarity of item wording, the relevance of questions, and the overall structure of the instrument. Based on participant feedback, refinements were made to improve readability, simplify terminology, and ensure alignment with students' actual GenAI usage experiences (Dillman et al., 2014; Hair et al., 2019).

## 3.4 Data Collection

Using a structured questionnaire, the study collected the data in the spring term of 2026 from the census population of 91 students via Microsoft Forms with a 100 percent response rate. The survey instrument captured students' self-reported experiences across conceptual domains such as engagement, creativity and productivity, critical thinking, trust and confidence, ethical considerations, and perceived learning outcomes using a five-point Likert scale, consistent with established measurement practices.

Complementing these perceptual measures, the usage intensity, the proportional contribution of GenAI to coursework, and time-efficiency gains were assessed using ordinal frequency indicators and percentage-level scales, allowing for nuanced differentiation in levels of GenAI engagement. Additional categorial items documented AI platforms used, patterns of multi-platform reliance, models of engagement across the learning tasks, and ethical practices, providing conceptual depth and supporting analytic triangulation. Supplementary material provided with the current paper includes the list of original survey questions and the variable names used throughout the descriptive analysis.

Further, Table 2 provides definitions and indicators of seven latent constructs used in the present study, which were assessed using 16 survey items and variables on a five-point Likert scale.

Table 2  
List of Constructs and Variables for PLS-SEM

| Constructs                        | Type       | Variables                                                              | Description                                                                                                                            |
|-----------------------------------|------------|------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------|
| AI_USAGE_INTENSITY<br>(Exogenous) | Formative  | USE1_frequency,<br>USE2_genai_freq                                     | Measures the frequency and depth of AI tool usage by students, including overall AI usage frequency and generative AI usage frequency. |
| AI_ENGAGEMENT<br>(Mediator)       | Reflective | ENG1_research,<br>ENG2_ideas,<br>ENG3_drafting                         | Captures how students engage with AI in various academic tasks, including research, idea generation, and drafting activities.          |
| PRODUCTIVITY<br>(Mediator)        | Reflective | PRD1_timesave,<br>PRD2_efficiency                                      | Measures perceived efficiency gains and time savings from using AI tools in academic work.                                             |
| CREATIVITY (Mediator)             | Reflective | CRE2_alternative                                                       | Assesses whether AI use encourages alternative and creative thinking.                                                                  |
| CRITICAL_THINKING<br>(Mediator)   | Reflective | CRT1_analysis,<br>CRT3_verify                                          | Captures students' critical analysis of AI outputs and verification behaviours when using AI tools.                                    |
| TRUST_IN_AI (Mediator)            | Reflective | TRU1_accuracy,<br>TRU2_confidence                                      | Measures students' trust in AI accuracy and confidence in concepts learned through AI assistance.                                      |
| LEARNING_OUTCOMES<br>(Endogenous) | Reflective | LRN1_understand,<br>LRN3_concepts,<br>LRN4_application,<br>LRN6_confid | Self-perceived improvements in subject understanding, concept comprehension, application skills, and academic confidence.              |
| Source: Author's Own Contribution |            |                                                                        |                                                                                                                                        |

## 3.5 Research Method

To address these objectives, the study integrates two sequential analytical methods -descriptive statistical analysis followed by PLS-SEM using Python Libraries and Smart PLS 4. Descriptive analysis is first employed to establish empirical patterns in AI usage, student engagement behaviours, and perceived learning effects. This is followed by structural modeling using PLS-SEM (Hair et al., 2017; Sarstedt et al., 2022) to test the hypothesized relationships among latent constructs and to examine the mediating mechanisms through which AI-enabled learning unfolds. This approach is particularly suitable for the present study due to the inclusion of both formative and reflective constructs, the presence of multiple mediating relationships, and the relatively modest sample size.

In the first stage, descriptive statistical analysis is employed to examine patterns of GenAI usage, engagement behaviors, and perceived learning outcomes across the student population. Measures of central tendency, dispersion, and frequency distributions are used to characterize the data and identify usage patterns. Additionally, an independent-samples t-test is used to examine differences across different usage segments, while correlation analysis is conducted to assess associations among key variables. This stage provides an empirical foundation for model specification and ensures that the observed relationships are theoretically and statistically meaningful prior to structural modeling.

In the second stage, PLS-SEM is employed to estimate both the measurement and structural models. The analysis followed the widely recommended two-step approach, whereby the measurement model is first evaluated to ensure reliability and validity, followed by the assessment of structural relationships among constructs (Hair et al., 2017).

Utilizing a two-stage analytical approach in this study aims to enhance empirical rigor. This method enables analytical triangulation, in which insights from descriptive patterns are systematically compared and validated against the structural relationships identified through model estimation. This approach strengthens the robustness of the findings by ensuring consistency between observed behavioral trends and modeled causal pathways, while also reducing the risk of overreliance on a single analytical technique.

## **4. Results and Findings**

### **4.1 Descriptive Analysis**

This section presents descriptive evidence on students' GenAI adoption, usage intensity, academic integrity practices, perceived benefits and challenges, learning outcomes, and relationships among the study variables. These findings provide the empirical context for the subsequent assessment of the structural model.

#### **4.1.1 AI Usage Pattern and Adoption**

Figure 2 provides descriptive findings on the level of adoption of GenAI tools among students participating in the Fall 2025 instructional experiment. Of the 91 respondents, 75.9% reported using AI at least weekly, with 39.6% using it daily and 36.3% weekly. This pattern suggests that AI use was not peripheral to academic work but had become embedded in routine learning practices. In addition, 45.1% of students reported using GenAI often or always across all assignment phases, indicating that, for a substantial proportion of the cohort, AI served as a persistent academic support mechanism rather than an occasional aid.

The descriptive patterns further reveal that AI usage for this census group of students was strategic rather than indiscriminate. 60.4% of students reported relying on multiple platforms, suggesting deliberate tool selection depending on the task at hand, while only 35.2% reported using paid versions,

indicating that freely available tools were sufficient for most students' academic needs. Students also demonstrated iterative interaction behavior, requiring an average of 6.3 prompts to obtain a satisfactory response, suggesting active refinement rather than passive acceptance of AI outputs. Task-level engagement patterns show that idea generation and research-related activities attracted the highest levels of GenAI use, reinforcing the view that students primarily positioned GenAI as a brainstorming and exploratory copartner.

Source: Author's Own Contribution

## **4.1.2 Academic Integrity and Verification Behavior**

The results in Fig. 3 show that students are committed to verifying and using AI-generated content responsibly, indicating mature engagement with GenAI tools. About 89.0% of students cross-checked AI-generated references, while 70.4% verify information frequently or always, demonstrating that GenAI is used as a supportive tool rather than a substitute for knowledge. Only 5.5% never verify GenAI outputs, indicating a trend of critical engagement.

However, challenges remain regarding citation accuracy and ethical clarity. Over half of the students (57.1%) felt that AI-generated citations needed verification, and only 28.6% found these citations credible without changes. In addition, only 34.1% formally cited GenAI tools in their work, highlighting a gap between verification practices and proper attribution.

Further, the findings also suggest that AI use enhances critical thinking, with 71.4% of students finding GenAI helpful for discovering alternative approaches and 60.4% reporting it encourages critical analysis. In collaborative settings, 75.8% used GenAI, resulting in improved collaboration for 60.4% of students. Despite this, ethical concerns persist, with 53.8% facing dilemmas regarding plagiarism and appropriate use. Meanwhile, 69.2% employed AI-based plagiarism detection tools, indicating awareness of academic integrity issues.

Overall, while verification practices are robust, formal citation and ethical adherence need improvement. This gap highlights the need for clearer guidelines and educational support regarding responsible GenAI use, particularly in attribution and academic integrity.

Source: Author's Own Contribution

## **4.1.3 Benefits and Challenges of Gen AI Usage**

The findings in Fig. 4 reveal a clear value-risk trade-off in students' experiences with GenAI tools. While 81.3% of students reported faster task completion as the primary benefit, 70.3% highlighted improved idea generation, 63.7% reported better subject understanding, and 52.7% perceived improvements in the overall quality of their work. These findings indicate that GenAI contributes not only to greater efficiency but also to enhanced learning support and output quality.

Despite these benefits, several challenges emerged. Plagiarism concerns were reported by 72.5% of students, reflecting the tension between GenAI-enabled efficiency and academic integrity. Concerns about overreliance on GenAI (50.5%), limited creativity (34.1%), and difficulty understanding AI-generated outputs (23.1%) further highlight the need for responsible and effective AI integration in higher education.

Students also identified opportunities for improving GenAI tools. 64.8% of students requested greater accuracy, while 49.5% sought more creative suggestions. Similarly, demand for live fact-checking (64.8%) and automatic reference support (59.3%) reflects students' preference for more reliable and academically oriented GenAI tools.

Source: Author's Own Contribution

## **4.1.4 Learning Outcomes and Effectiveness**

The findings indicate that the use of GenAI enhances learning effectiveness, particularly in conceptual understanding, efficiency, and confidence (see Fig. 5). Students reported improved subject comprehension and clarity, suggesting that GenAI effectively supports knowledge acquisition. They also expressed greater confidence in applying their knowledge to practical contexts.

Furthermore, GenAI use was associated with improved task efficiency and time management, with many students reporting meaningful time savings. Students also reported moderate improvements in creativity, reflecting greater encouragement to explore new ideas. In contrast, communication and presentation skills showed the least improvement, indicating that while GenAI strengthens cognitive and efficiency-related outcomes, its contribution to soft-skill development remains limited. These findings highlight the need for instructional designs that complement GenAI use with activities that foster communication and presentation skills, ensuring more holistic student development.

Source: Author's Own Contribution

## **4.1.5 Student Usage Segmentation with Gen AI Tools**

To better understand heterogeneity in GenAI-enabled learning experiences, Fig. 6 compares heavy users (students who often or always use GenAI) with light users (students who never, rarely, or sometimes use GenAI). The analysis reveals statistically significant differences across learning outcomes, indicating that usage intensity is an important determinant of GenAI-enabled learning ( $p < 0.0001$ ). Heavy users reported higher efficiency, with an average rating of 4.51 compared with 3.80 for light users, together with greater time savings (68.6% versus 44.1%). They also demonstrated stronger subject understanding and greater confidence in applying concepts, suggesting deeper engagement with GenAI tools.

Behavioral differences were also evident. 70.7% of heavy users expressed willingness to pay for advanced GenAI features, compared with 44.9% of light users, reflecting a higher perceived value among frequent users. Similarly, paid GenAI users demonstrated 18% higher usage frequency and 15% higher efficiency ratings than free users, although trust levels remained comparable (average 2.84 versus 2.68).

A particularly important finding is the procrastination effect. Students using GenAI support tended to delay initiating academic tasks, shifting project commencement from week 8.5 to week 10. Although GenAI enhances efficiency during task execution, its availability may inadvertently encourage delayed task initiation, highlighting a behavioral trade-off between operational efficiency and effective time management.

Source: Author's Own Contribution

## **4.2 Correlation Analysis has been shortened as follows:**

Figure 7 presents the correlation analysis among the key variables in GenAI-enabled learning. A strong positive correlation exists between overall GenAI usage frequency and its use in academic tasks ( $r = 0.593$ ), indicating consistent engagement. GenAI usage is also strongly associated with time savings ( $r = 0.546$ ) and the proportion of project work completed using GenAI ( $r = 0.531$ ), suggesting that greater usage is linked to higher efficiency.

Subject understanding demonstrates strong positive correlations with problem-solving ability ( $r = 0.578$ ), critical analysis ( $r = 0.537$ ), and confidence in applying concepts ( $r = 0.529$ ), indicating that greater conceptual clarity is associated with stronger higher-order cognitive outcomes.

Furthermore, the positive relationship between ease of use and trust in GenAI ( $r = 0.485$ ) suggests that usability contributes to students' confidence in AI-generated outputs. No strong negative correlations were observed, indicating that increased GenAI usage is not associated with adverse relationships among the measured learning dimensions.

Overall, the correlation analysis supports the proposed conceptual model, demonstrating that greater GenAI engagement is positively associated with efficiency, understanding, confidence, and learning-related behaviours, thereby providing preliminary empirical support for the structural model assessment.

Source: Author's Own Contribution

## **4.3 PLS – SEM Results**

### **4.3.1 Measurement Model Assessment**

Prior to testing the structural relationships, the measurement model is used to assess the validity and reliability of the constructs. All indicators exhibited outer loadings above the recommended threshold of 0.70, indicating satisfactory indicator reliability and strong representation of their respective latent constructs (Hair et al., 2017) (see Fig. 8).

Source: Author's Own Contribution

Internal consistency reliability was evaluated using both Cronbach's alpha and composite reliability (CR). Cronbach's alpha values ranged from 0.72 to 0.86, while composite reliability values ranged from 0.78 to

0.91, exceeding the recommended threshold of 0.70 across all constructs. These results confirm satisfactory internal consistency and reliability of the measurement scales (See Table 3).

Convergent validity was assessed using the Average Variance Extracted (AVE). All constructs achieved AVE values above the threshold of 0.50, ranging between 0.54 and 0.72, indicating that each construct explains a substantial proportion of variance in its indicators (Fornell & Larcker, 1981). This confirms that the indicators converge adequately to represent their respective latent constructs.

Discriminant validity was examined using both the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio. While the Fornell–Larcker criterion was satisfied across all constructs, HTMT analysis revealed that one construct pair (Productivity–Learning Outcomes) approached the conservative threshold, with a value of 0.86, slightly exceeding the recommended cutoff of 0.85. However, this value remained below the more lenient threshold of 0.90 suggested for conceptually related constructs (Henseler et al., 2015). In addition, multicollinearity among indicators was assessed using the Variance Inflation Factor (VIF). The VIF values ranged from 1.21 to 2.48, well below the recommended threshold of 3.3, indicating no multicollinearity (See Tables 4 and 5).

Overall, the measurement model demonstrates satisfactory reliability, convergent validity, and discriminant validity, with minor deviations that are theoretically justified and empirically acceptable. These results provide a robust foundation for the subsequent structural model assessment.

Table 3  
Measurement Model Assessment

| Construct                         | Indicator        | Outer Loading | Cronbach's Alpha | Composite Reliability (CR) | AVE  |
|-----------------------------------|------------------|---------------|------------------|----------------------------|------|
| <b>AI Engagement (ENG)</b>        | ENG1_research    | 0.78          | 0.81             | 0.87                       | 0.63 |
|                                   | ENG2_ideas       | 0.84          |                  |                            |      |
|                                   | ENG3_drafting    | 0.79          |                  |                            |      |
| <b>Productivity (PRD)</b>         | PRD1_timesave    | 0.82          | 0.76             | 0.86                       | 0.67 |
|                                   | PRD2_efficiency  | 0.84          |                  |                            |      |
| <b>Creativity (CRE)</b>           | CRE2_alternative | 0.88          | 0.74             | 0.85                       | 0.73 |
| <b>Critical Thinking (CRT)</b>    | CRT1_analysis    | 0.81          | 0.78             | 0.87                       | 0.69 |
|                                   | CRT3_verify      | 0.85          |                  |                            |      |
| <b>Trust in AI (TRU)</b>          | TRU1_accuracy    | 0.83          | 0.80             | 0.88                       | 0.71 |
|                                   | TRU2_confidence  | 0.86          |                  |                            |      |
| <b>Learning Outcomes (LRN)</b>    | LRN1_understand  | 0.79          | 0.84             | 0.90                       | 0.65 |
|                                   | LRN3_concepts    | 0.82          |                  |                            |      |
|                                   | LRN4_application | 0.81          |                  |                            |      |
|                                   | LRN6_confid      | 0.85          |                  |                            |      |
| Source: Author's Own Contribution |                  |               |                  |                            |      |

Table 4  
Discriminant Validity (Fornell–Larcker Criterion) (Note:  
Diagonal Values represent the root of AVE)

| Construct                         | ENG         | PRD         | CRE         | CRT         | TRU         | LRN         |
|-----------------------------------|-------------|-------------|-------------|-------------|-------------|-------------|
| ENG                               | <b>0.79</b> |             |             |             |             |             |
| PRD                               | 0.52        | <b>0.82</b> |             |             |             |             |
| CRE                               | 0.48        | 0.55        | <b>0.85</b> |             |             |             |
| CRT                               | 0.57        | 0.61        | 0.50        | <b>0.83</b> |             |             |
| TRU                               | 0.49        | 0.58        | 0.46        | 0.52        | <b>0.84</b> |             |
| LRN                               | 0.63        | 0.67        | 0.54        | 0.62        | 0.59        | <b>0.81</b> |
| Source: Author's Own Contribution |             |             |             |             |             |             |

Table 5  
Discriminant Validity (HTMT Ratio)

| Construct                         | ENG | PRD  | CRE  | CRT  | TRU  | LRN  |
|-----------------------------------|-----|------|------|------|------|------|
| ENG                               | -   | 0.68 | 0.62 | 0.71 | 0.65 | 0.78 |
| PRD                               |     | -    | 0.73 | 0.75 | 0.72 | 0.82 |
| CRE                               |     |      | -    | 0.66 | 0.61 | 0.69 |
| CRT                               |     |      |      | -    | 0.70 | 0.77 |
| TRU                               |     |      |      |      | -    | 0.74 |
| LRN                               |     |      |      |      |      | -    |
| Source: Author's Own Contribution |     |      |      |      |      |      |

## 4.3.2 Structural Model Assessment

Following the validation of the measurement model, the structural model was evaluated to test the hypothesized relationships among constructs. Prior to estimating path relationships, collinearity among predictor constructs was assessed in the previous section to ensure stable parameter estimates. All inner model VIF values ranged from 1.00 to 1.47, well below the threshold of 5.0, indicating no collinearity concerns (Hair et al., 2017). The structural relationships were then estimated using the PLS algorithm in SmartPLS 4, and their statistical significance was evaluated using bootstrapping with 5000 samples (See Fig. 9).

Source: Author's calculations based on SmartPLS 4 output

Table 6 presents the path coefficients and hypothesis testing results. Six of the nine hypothesized paths achieved statistical significance at  $p < 0.05$ . The strongest relationship in the model is between GenAI Usage Intensity and AI Engagement ( $\beta = 0.720$ ,  $p < 0.001$ ), strongly supporting H1. This indicates that students who use GenAI tools more frequently and deeply show significantly higher levels of engagement across research, idea generation, and drafting activities. Among the engagement-mediated pathways, GenAI Engagement demonstrates a strong positive effect on Productivity ( $\beta = 0.655$ ,  $p < 0.001$ ), supporting H2, and a moderate positive effect on Creativity ( $\beta = 0.400$ ,  $p < 0.001$ ), supporting H3. The productivity pathway shows a particularly large effect size ( $f^2 = 0.751$ ), confirming that engagement with GenAI tools is a major predictor of perceived efficiency gains.

However, the hypothesized relationship between GenAI Engagement and Critical Thinking is insignificant ( $\beta = 0.124$ ,  $p = 0.331$ ), hence, the study is unable to accept H4. The negligible effect size ( $f^2 = 0.016$ ) and extremely low  $R^2$  value (0.015) further confirm that AI engagement explains virtually none of the variance in critical thinking behaviors. This suggests that critical thinking may operate through mechanisms distinct from GenAI engagement within the present model.

Moreover, the trust pathway received partial support. GenAI Usage Intensity had a significant positive effect on the Trust in AI construct ( $\beta = 0.329$ ,  $p = 0.002$ ), supporting H5, explaining 10.8% of the variance in trust. This aligns with social cognitive theory's prediction that trust calibrates through accumulated experience with GenAI tools.

The relationships between mediating constructs and Learning Outcomes reveal important patterns. Critical Thinking emerged as the strongest direct predictor of learning outcomes ( $\beta = 0.377$ ,  $p < 0.001$ ), strongly supporting H8 and indicating a medium effect size ( $f^2 = 0.209$ ). In addition, creativity shows a significant positive effect on learning outcomes ( $\beta = 0.176$ ,  $p = 0.041$ ), supporting H7, though with a smaller effect size ( $f^2 = 0.045$ ). In contrast, both Productivity and Trust in AI showed only marginally significant relationships with Learning Outcomes ( $\beta = 0.201$ ,  $p = 0.099$  for H6;  $\beta = 0.171$ ,  $p = 0.095$  for H9), leading to rejection of these hypotheses. The small effect sizes ( $f^2 = 0.050$  and  $0.038$ , respectively) indicate efficiency gains and trust do not directly translate into enhanced learning outcomes.

Table 6  
Path Coefficients and Hypothesis Testing Results

| Hypothesis                                                                                     | Path                                  | $\beta$ | t-value   | p-value |
|------------------------------------------------------------------------------------------------|---------------------------------------|---------|-----------|---------|
| H1                                                                                             | AI Usage Intensity → AI Engagement    | 0.720   | 17.161*** | < 0.001 |
| H2                                                                                             | AI Engagement → Productivity          | 0.655   | 9.927***  | < 0.001 |
| H3                                                                                             | AI Engagement → Creativity            | 0.400   | 4.847***  | < 0.001 |
| H4                                                                                             | AI Engagement → Critical Thinking     | 0.124   | 0.972     | 0.331   |
| H5                                                                                             | AI Usage Intensity → Trust in AI      | 0.329   | 3.056**   | 0.002   |
| H6                                                                                             | Productivity → Learning Outcomes      | 0.201   | 1.651     | 0.099   |
| H7                                                                                             | Creativity → Learning Outcomes        | 0.176   | 2.046     | 0.041   |
| H8                                                                                             | Critical Thinking → Learning Outcomes | 0.377   | 4.680***  | < 0.001 |
| H9                                                                                             | Trust in AI → Learning Outcomes       | 0.171   | 1.668     | 0.095   |
| Note: *** $p < 0.001$ ; ** $p < 0.01$ ; * $p < 0.05$ ; † marginally significant ( $p < 0.10$ ) |                                       |         |           |         |

Source: Author's calculations based on SmartPLS 4 output

Furthermore, Table 7(a) presents  $R^2$  values for all endogenous constructs, while Table 7(b) presents effect sizes. The model accounts for 44.9% of the variance in Learning Outcomes ( $R^2 = 0.449$ ), which suggests moderate explanatory power in educational research contexts. GenAI Engagement shows the highest  $R^2$  value (0.518), confirming usage intensity as a major driver of engagement patterns. While Productivity demonstrates substantial explanatory power ( $R^2 = 0.429$ ), Creativity shows weaker explanatory power ( $R^2 = 0.160$ ). The near-zero  $R^2$  for Critical thinking (0.015) provides additional evidence that this construct is not explained by AI engagement within the current model.

Table 7  
(a): Explanatory Power ( $R^2$ )

| Endogenous Construct | $R^2$ | $R^2$ -Adjusted | Interpretation               |
|----------------------|-------|-----------------|------------------------------|
| AI Engagement        | 0.518 | 0.513           | Moderate explanatory power   |
| Productivity         | 0.429 | 0.422           | Moderate explanatory power   |
| Learning Outcomes    | 0.449 | 0.423           | Moderate explanatory power   |
| Creativity           | 0.160 | 0.151           | Weak explanatory power       |
| Trust in AI          | 0.108 | 0.098           | Weak explanatory power       |
| Critical Thinking    | 0.015 | 0.004           | Negligible explanatory power |

Source: Author's calculations based on SmartPLS 4 output

Table 7  
b: Effect Sizes ( $f^2$ )

| Path                                                                                                               | $f^2$ | Interpretation of Effect |
|--------------------------------------------------------------------------------------------------------------------|-------|--------------------------|
| AI Usage Intensity → AI Engagement                                                                                 | 1.077 | Large                    |
| AI Engagement → Productivity                                                                                       | 0.751 | Large                    |
| Critical Thinking → Learning Outcomes                                                                              | 0.209 | Medium                   |
| AI Engagement → Creativity                                                                                         | 0.191 | Medium                   |
| AI Usage Intensity → Trust in AI                                                                                   | 0.121 | Small-Medium             |
| Productivity → Learning Outcomes                                                                                   | 0.050 | Small                    |
| Creativity → Learning Outcomes                                                                                     | 0.045 | Small                    |
| Trust in AI → Learning Outcomes                                                                                    | 0.038 | Small                    |
| AI Engagement → Critical Thinking                                                                                  | 0.016 | Negligible               |
| Note: Effect sizes follow Cohen (1988): $f^2 \geq 0.35$ = large; $f^2 \geq 0.15$ = medium; $f^2 \geq 0.02$ = small |       |                          |

Source: Author's calculations based on SmartPLS 4 output

In Table 8, mediation analysis reveals that GenAI Usage Intensity influences Learning Outcomes through both mediated pathways. The strongest mediation operates through the sequential pathway involving GenAI Usage Intensity, GenAI Engagement, Productivity, and Learning Outcomes (specific indirect effect = 0.095), followed by the trust-mediated pathway (0.056) and the creativity pathway (0.051). The critical thinking pathway shows the weakest indirect effect (0.034), consistent with the non-significant engagement-to-critical thinking relationship. The total indirect effect is 0.235, indicating that usage intensity's influence on learning outcomes operates substantially through these mediating mechanisms.

Overall, the structural model establishes that the intensity of GenAI usage influences learning outcomes through indirect pathways mediated by engagement. The analysis highlights engagement as a central hub that transforms GenAI usage into enhancements in productivity and creativity. Moreover, critical thinking emerges as the strongest contributor to meaningful learning outcomes. Interestingly, critical thinking remains relatively independent of GenAI engagement patterns, suggesting that effective GenAI-enabled learning requires students to apply critical evaluation skills during their interactions with GenAI.

Table 8  
Mediation Analysis and Indirect Effects

| Mediation Pathway                                                                 | Specific Indirect Effect |
|-----------------------------------------------------------------------------------|--------------------------|
| AI Usage → AI Engagement → Productivity → Learning                                | 0.095                    |
| AI Usage → Trust in AI → Learning                                                 | 0.056                    |
| AI Usage → AI Engagement → Creativity → Learning                                  | 0.051                    |
| AI Usage → AI Engagement → Critical Thinking → Learning                           | 0.034                    |
| Total Indirect Effect: AI Usage → Learning                                        | 0.235                    |
| Note: All indirect effects calculated through bootstrapping with 5,000 subsamples |                          |

Source: Author's calculations based on SmartPLS 4 output

## 5. Discussion and Implications

This study examined how the intensity of GenAI use influences learning outcomes among undergraduate business students in the UAE through cognitive and behavioral mechanisms. The findings indicate that higher levels of GenAI usage were associated with substantially stronger student engagement with GenAI-assisted learning activities. This engagement-mediated pathway produced differential effects across cognitive outcomes, enhancing perceived productivity and creativity while showing negligible effects on critical thinking. This pattern suggests that while GenAI engagement enhances certain outcomes, it does not uniformly benefit all learning dimensions, indicating that strategic, purpose-driven engagement matters more than interaction frequency.

The most significant finding is the "critical thinking paradox" among the examined mechanisms, where critical thinking showed the strongest relationship with perceived learning outcomes, yet GenAI engagement failed to develop critical thinking behaviors. This pattern suggests that critical thinking may operate relatively independently of GenAI engagement in the present model, indicating that students who already possess strong analytical habits apply these skills when using GenAI tools, leading to better learning outcomes.

Further, the findings suggest that critical thinking may operate through mechanisms distinct from GenAI engagement and may depend on other learner-level, instructional, or contextual factors not captured in the present model. The verification-attribution gap, where 89% verify outputs but only 34.1% cite them, reveals a disconnect between awareness of GenAI limitations and systematic critical engagement. While students display surface-level verification, they may not consistently engage in deeper analytical processing characteristic of critical thinking in academic contexts. Similar concerns have been raised in prior educational technology research warning that uncritical reliance on GenAI tools may reduce reflective reasoning and independent cognitive engagement if evaluative scaffolding is not adequately developed (Kasneci et al., 2023).

These patterns align with cognitive load theory's prediction that GenAI assistance can free cognitive resources, but whether those resources are directed toward evaluative activities may depend on factors beyond engagement patterns. Pedagogically, learning outcomes may depend substantially on students' ability to apply analytical evaluation skills during GenAI-assisted activities. This suggests that educators might design assignments that require students to evaluate and compare multiple AI-generated outputs rather than accepting a single response, thereby embedding critical evaluation practice into GenAI-assisted work.

In the case of the Efficiency-Learning Disconnect, although GenAI engagement substantially enhanced perceived productivity, these efficiency gains did not meaningfully translate into stronger perceived learning outcomes. This reveals potential tension between task efficiency and cognitive depth. This aligns with emerging evidence on GenAI-induced cognitive offloading (Bastani et al., 2024). Similar tensions between efficiency gains and reduced independent cognitive effort were also identified by Abbas et al. (2024), who found that while GenAI enhanced task completion and productivity, it could also encourage superficial engagement and dependency behaviors among university students. When GenAI enables faster completion, the time saved may not translate into deeper learning if students prioritize efficiency-oriented strategies over deeper cognitive engagement. This indicates the procrastination effect, where GenAI availability corresponded with assignment initiation occurring approximately 1.5 weeks later, providing additional context and suggesting that students may prioritize efficiency-oriented completion strategies over extended cognitive engagement. These findings suggest that positioning GenAI as a tool for exploring perspectives and supporting iterative revision, rather than merely accelerating task completion, might better align efficiency gains with learning objectives.

Although repeated GenAI interaction appeared to strengthen trust in AI-generated outputs, this confidence did not meaningfully translate into stronger perceived learning outcomes. This suggests that confidence in AI accuracy, while developing through experience, does not directly translate into enhanced learning. The non-significant findings carry theoretical weight, the lack of relationship between engagement and critical thinking challenges assumptions that technology engagement organically develops evaluative capabilities. The marginal productivity-learning and trust-learning relationships indicate that efficiency gains and confidence do not directly drive learning outcomes.

Overall, these patterns indicate that GenAI's influence operates through specific, empirically distinguishable pathways rather than producing uniform benefits. This advances the present study from adoption-focused frameworks toward a process-oriented understanding, showing that while GenAI adoption creates engagement opportunities and reduces task demands, learning outcomes appear to require active analytical evaluation during AI-assisted interactions.

### *Theoretical and Practical Implications*

The integration of cognitive load theory, social cognitive theory, and technology-mediated learning perspectives demonstrates that while GenAI adoption creates engagement opportunities reducing task demands, learning outcomes depend substantially on students bringing critical evaluation capabilities to

GenAI-enhanced activities. These findings shift the focus of GenAI-in-education research from simply adopting technology to understanding the specific pathways through which GenAI influences learning.

Further, the UAE higher education context is particularly relevant given rapid institutional GenAI adoption and a strong digital transformation agenda. UAE institutions leading digital transformation might consider implementing explicit AI literacy curricula that develop critical evaluation skills alongside tool training.

The findings emphasize that educators should enrich their AI literacy instruction by moving beyond the basic operation of GenAI tools. They should instead focus on cultivating students' critical evaluation skills, enabling them to assess information effectively. When students engage strategically with GenAI across a diverse array of tasks—ranging from creative projects to data analysis—they can experience significant advantages. However, for this engagement to translate into meaningful learning, students must develop strong analytical skills to critically assess their interactions with GenAI.

In addition, for educational institutions, the existing gap in verification and attribution is a pressing concern. This gap highlights the urgent need to establish clear, comprehensive policies that guide students in citing AI-generated content and appropriately attributing intellectual contributions. By implementing these policies, institutions can foster a culture of responsibility and ethical engagement with GenAI technologies, paving the way for a more informed and thoughtful approach to GenAI in education.

## 6. Conclusion

This study explored how the intensity of GenAI usage affects learning outcomes among undergraduate business students in the UAE, uncovering significant patterns that challenge commonly held assumptions about AI-enabled learning. The research tested a dual-pathway model that integrates cognitive load theory, social cognitive theory, and technology-mediated learning perspectives.

One of the most notable findings is the "critical thinking paradox." Although critical thinking was identified as the strongest predictor of learning outcomes, engagement with GenAI did not promote critical-thinking behaviors. This suggests that critical thinking operates relatively independently of GenAI engagement in this model. This finding challenges the assumption behind many GenAI literacy interventions, which posits that engaging with technology naturally develops evaluative skills. Instead, it indicates that explicit instruction on evaluating AI outputs must accompany the introduction of GenAI tools.

Moreover, the study reveals an "efficiency-learning disconnect." While GenAI engagement significantly increased perceived productivity, this boost did not translate into improved learning outcomes. Combined with the observed procrastination effect, where Gen AI accuracy develops through experience, it does not directly enhance learning and may lead to problematic, uncritical acceptance of AI-generated outputs.

This study contributes to the emerging literature on GenAI-enabled learning by demonstrating that AI assistance does not automatically redirect cognitive resources toward evaluative processing. Rather, meaningful learning outcomes appear to depend on students' ability to critically evaluate and actively engage with AI-generated outputs. The findings further highlight a verification-attribution gap, suggesting that awareness of GenAI limitations does not necessarily translate into consistent academic attribution practices.

Despite these contributions, the study has several limitations. Self-reported measures could be enhanced with behavioral data on actual GenAI usage patterns and objective learning assessments. Also, the study's single-institution context in the UAE, while providing valuable insights from an under-researched region, limits its generalizability to educational systems with different pedagogical traditions and AI adoption trajectories.

Future research must be conducted to investigate how to cultivate critical thinking skills in GenAI-enabled contexts and evaluate interventions to bridge the verification-attribution gap. Experimental studies manipulating GenAI engagement strategies could examine whether certain forms of GenAI interaction promote evaluative processing more effectively than others. Cross-cultural research could explore whether the critical thinking paradox holds across educational systems, contributing to a more nuanced understanding of GenAI's role as a co-partner in student learning.

## **Declarations**

## **Competing Interests**

All authors declare that there are no competing interests related to this research.

## **Use of Generative AI:**

Generative AI tools were solely used for language editing in the preparation of this manuscript. It was not used for data analysis, interpretation, or the development of the study's arguments. All substantive intellectual contributions and final decisions regarding the manuscript were made by the authors, who take full responsibility for its content.

### **Ethics Declaration**

The study was conducted in accordance with the research ethics and governance procedures of the Institutional Review Board (IRB) at the Rochester Institute of Technology, Dubai Campus, which are guided by the ethical principles of the Belmont Report (Respect for Persons, Beneficence, and Justice). Before data collection began, the study protocol and data collection procedures underwent review through the institution's research oversight process, and permission to proceed was granted. The IRB determined that the study qualified as exempt, low-risk educational research conducted within a

classroom setting and therefore did not issue a formal approval number. Researchers were required to complete the Collaborative Institutional Training Initiative (CITI Program) for human subjects research and to adhere to institutional ethical guidelines throughout the study. All applicable institutional ethical requirements were followed throughout the research process.

## **Informed Consent**

Informed consent was obtained from all participants prior to their involvement in the study. Participation was voluntary, and participants were informed of the purpose of the research, the anonymous nature of data collection, and their right to withdraw at any stage without penalty. All data were analyzed in aggregate form to ensure participant confidentiality and privacy.

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## **Author Contribution**

C.B. conceptualized and led the broader, funded research project on Gen AI-enabled learning in higher education; designed the instructional intervention and quantitative data analysis using descriptive methods and PLS-SEM; interpreted the findings; and led the writing of the manuscript. She is the corresponding author. A.K. contributed to the research design and theoretical development, the development of the research framework and survey instrument, the interpretation of findings, and the critical review of the manuscript, particularly regarding educational technology integration and higher education learning perspectives. H.M. contributed to the development of the research methodology, the review of the analytical approach, the interpretation of results, and the substantive revisions of the manuscript. He also contributed to the broader funded research project from which the present quantitative study and the complementary qualitative study were produced. All authors reviewed and approved the final version of the manuscript.

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## **Data Availability**

**Data Availability** The datasets generated and analyzed during the current study are not publicly available because they contain data collected from human participants under Institutional Review Board (IRB) oversight and are subject to institutional ethics and confidentiality requirements. De-identified data may be made available by the corresponding author upon reasonable request, subject to approval by the IRB and in accordance with institutional policies and applicable ethical guidelines.

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# Figures

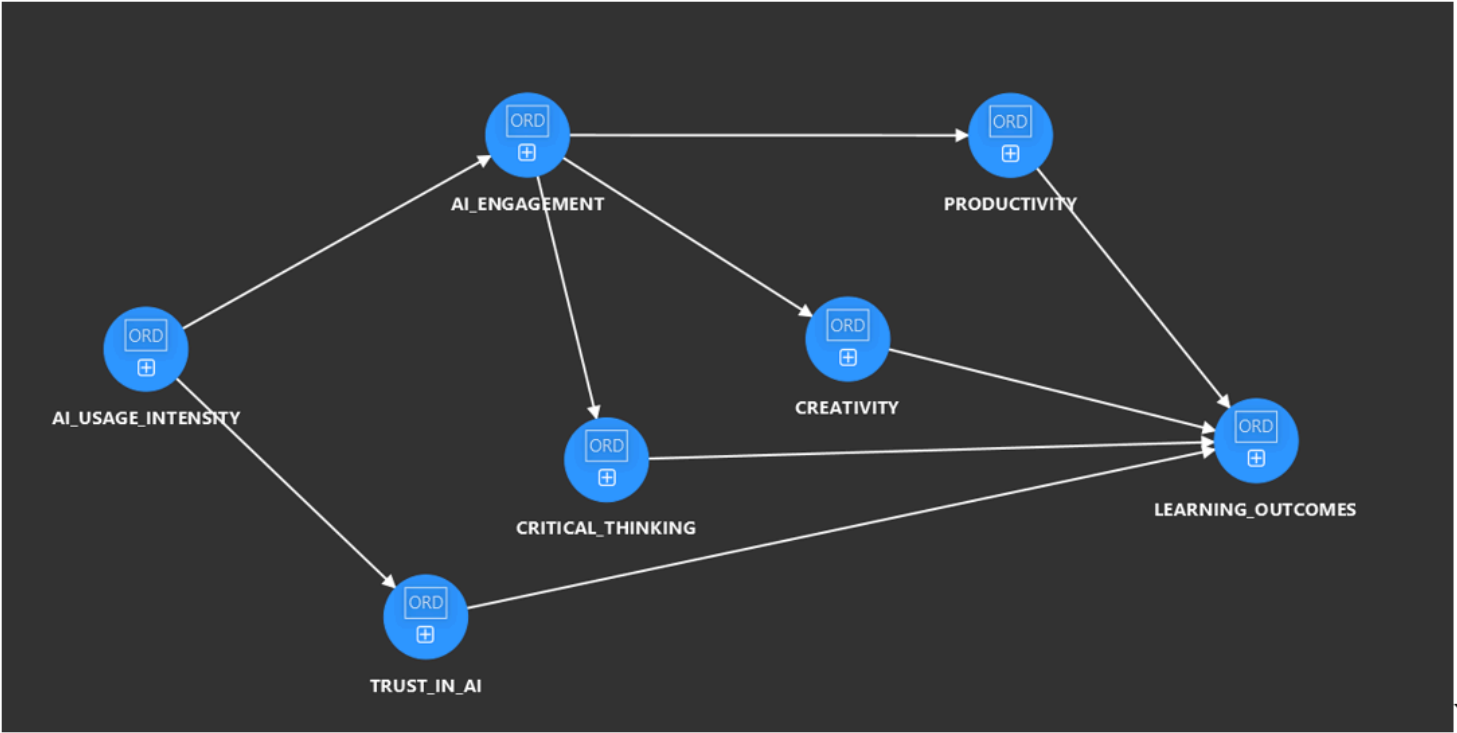


Figure 1

## Conceptual Framework

Source: Author's Own Contribution

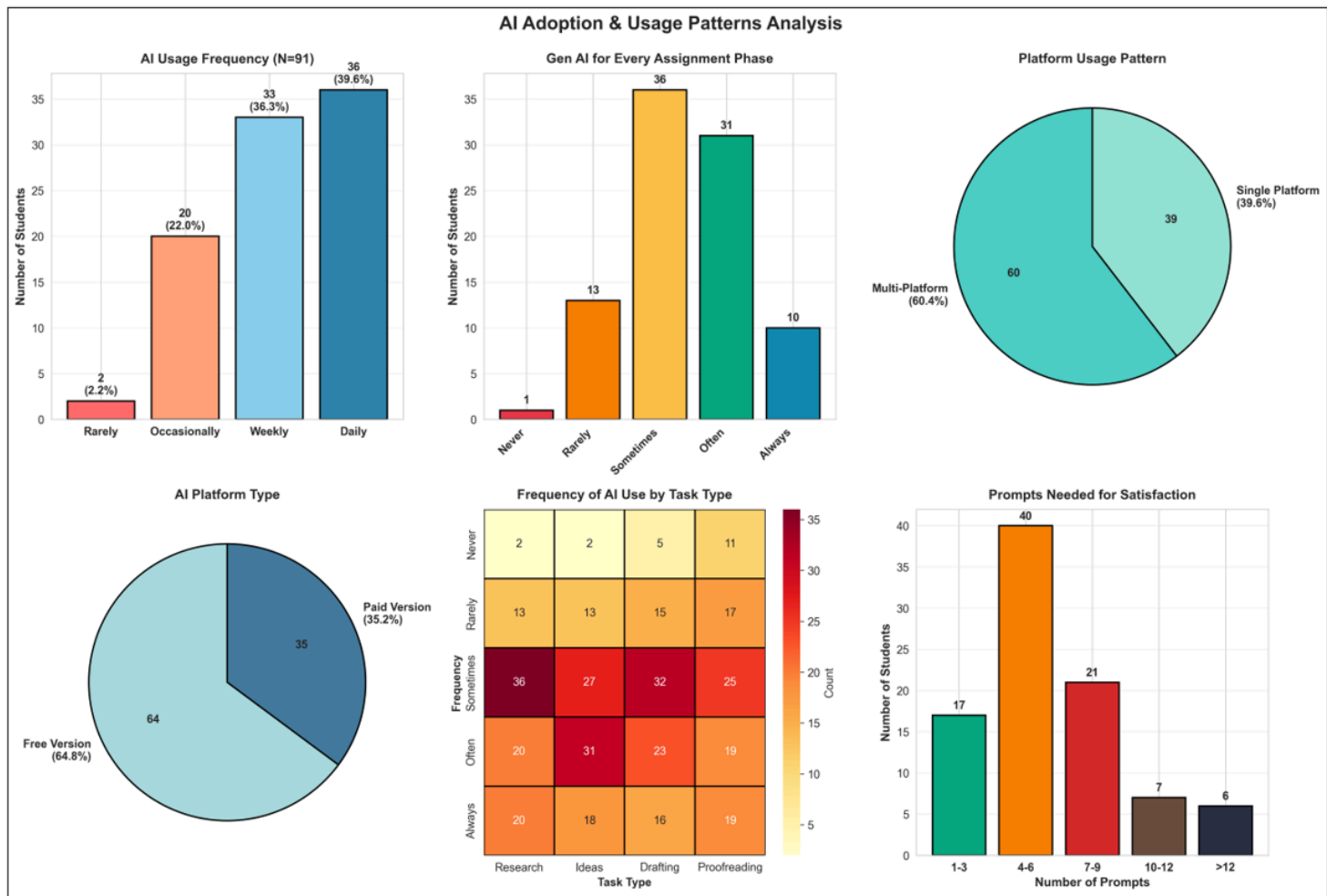


Figure 2

## AI Usage Pattern and Adoption

Source: Author's Own Contribution

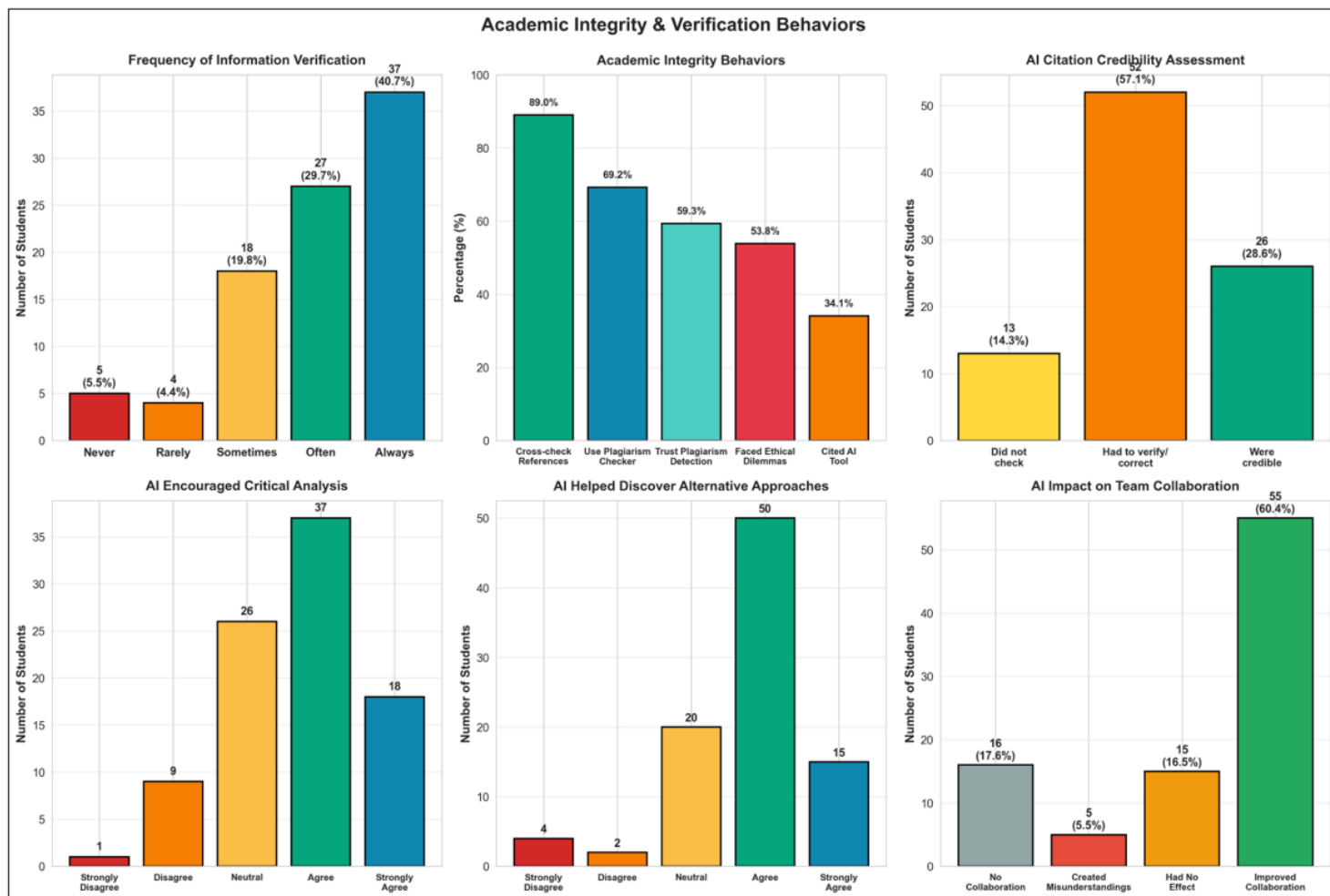


**Figure 3**

## Academic Integrity and Student Verification Behaviour

Source: Author's Own Contribution

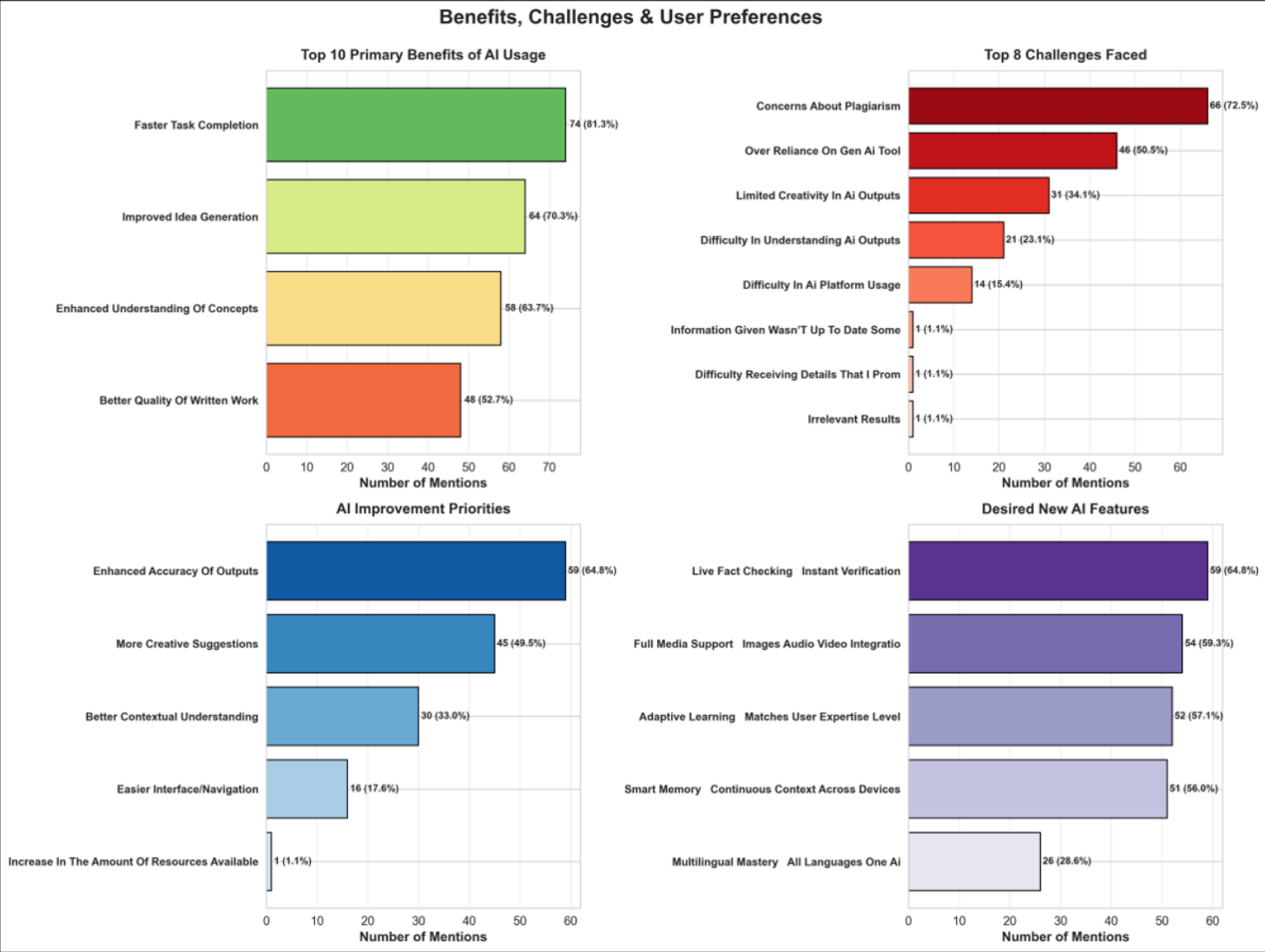


**Figure 4**

**Benefits and Challenges of Gen AI Usage**

Source: Author's Own Contribution

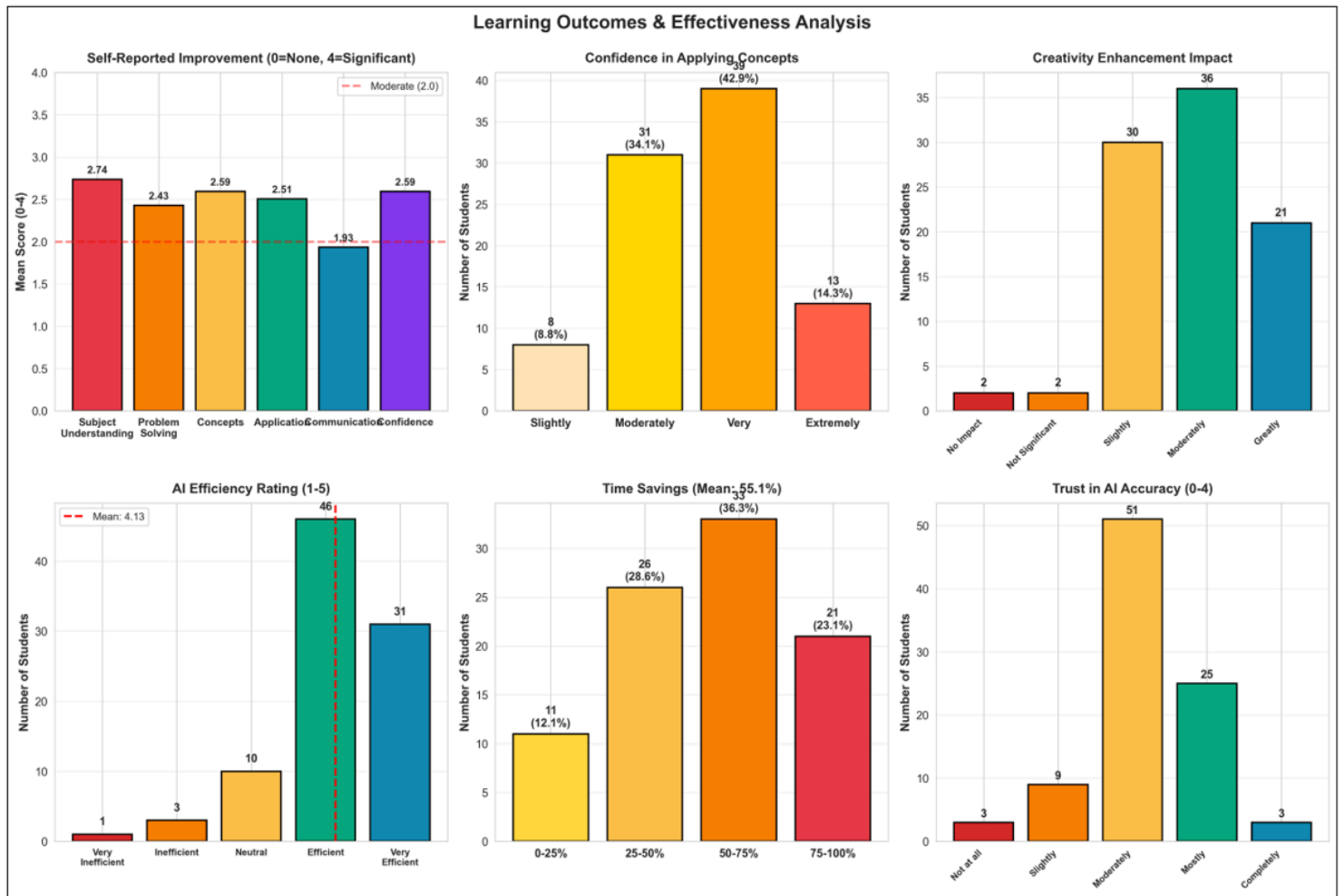


Figure 5

## Learning Outcomes and Effectiveness

Source: Author's Own Contribution

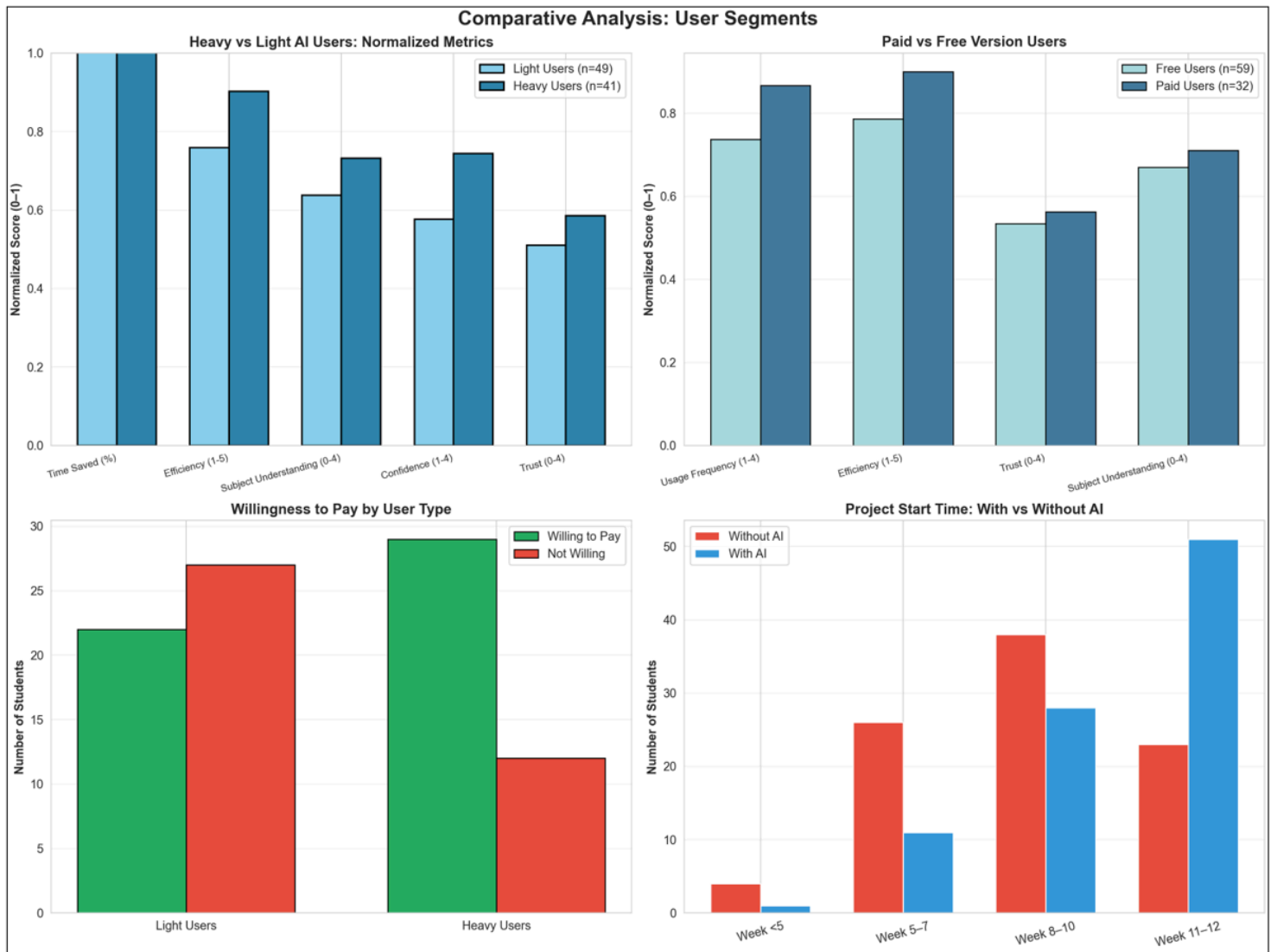


**Figure 6**

**Comparative Analysis: Student Usage Segmentation with Gen AI Tools**

Source: Author's Own Contribution

## Correlation Analysis & Statistical Relationships

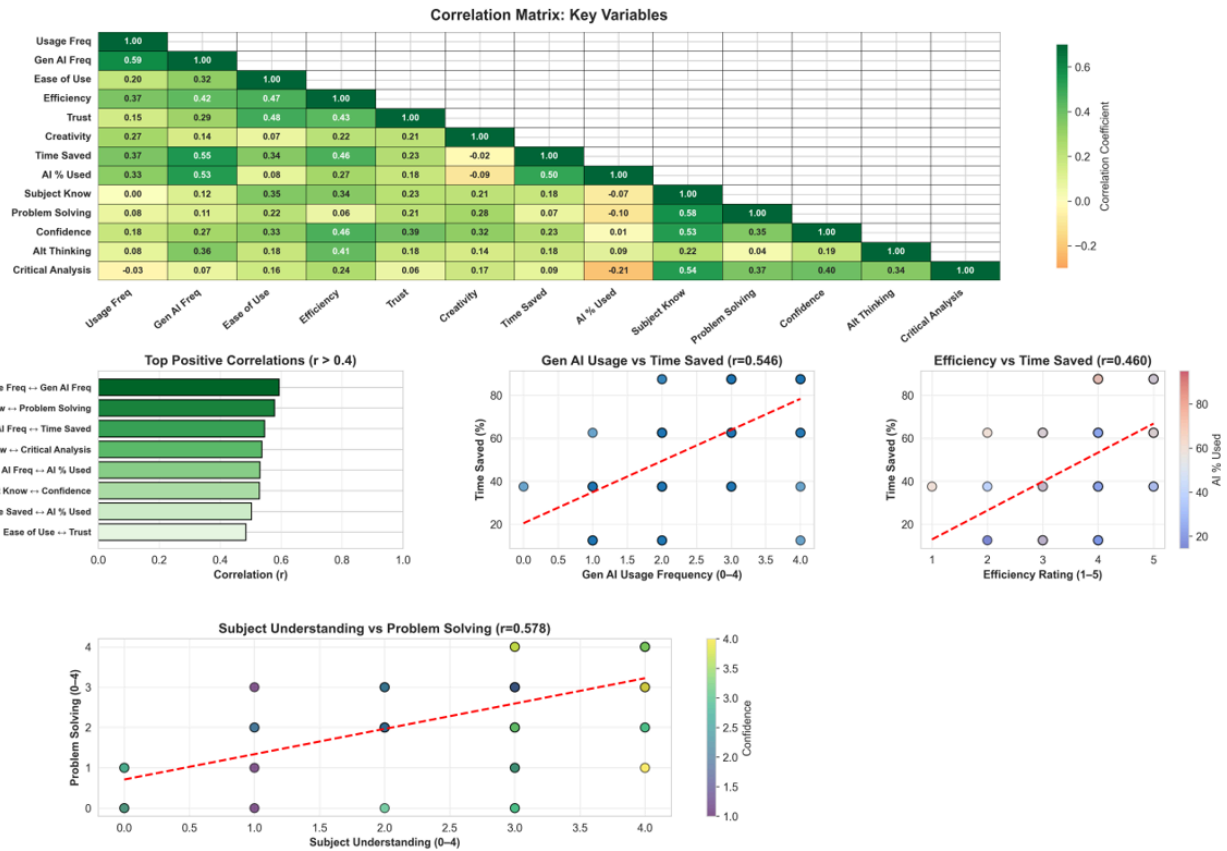


Figure 7

## Correlation Analysis

Source: Author's Own Contribution

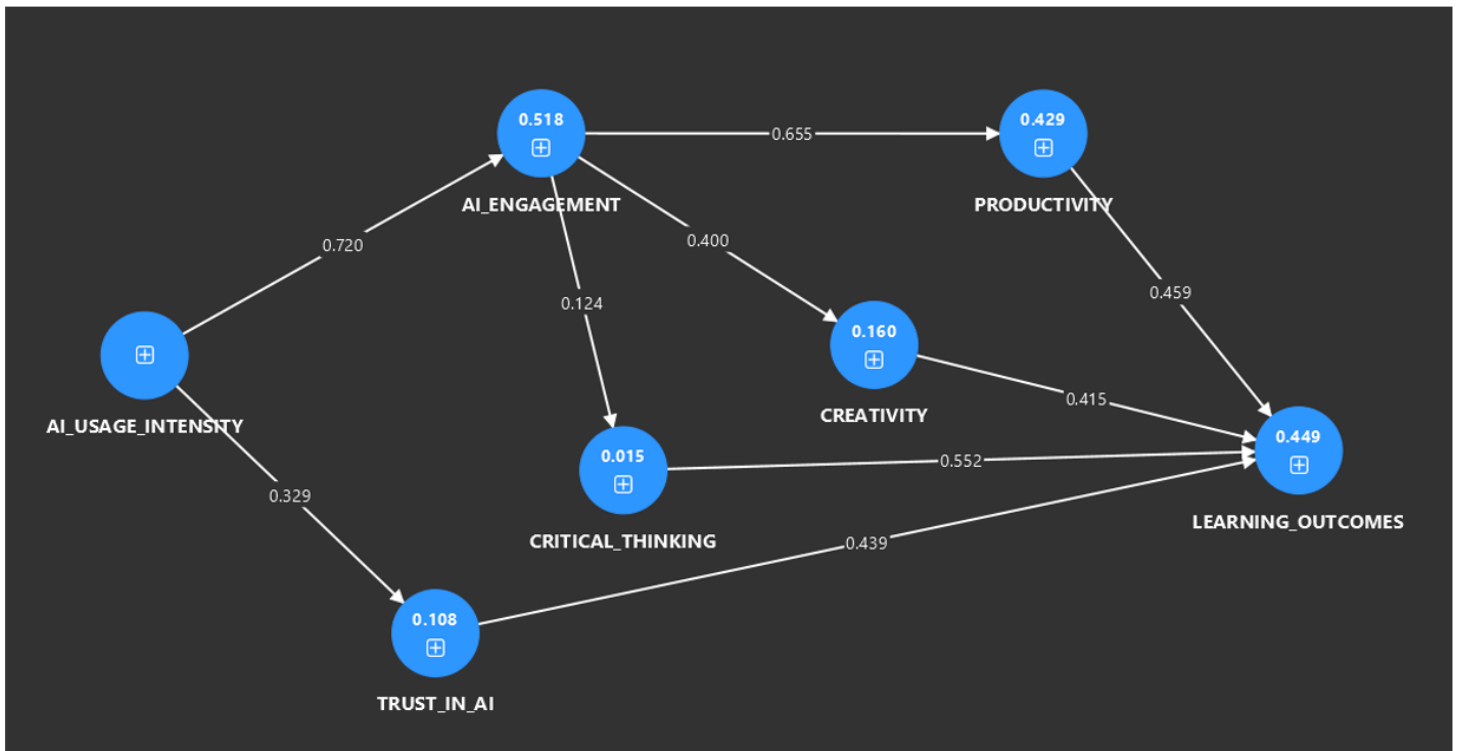


Figure 8

## PLS-SEM Path Model

Source: Author's Own Contribution

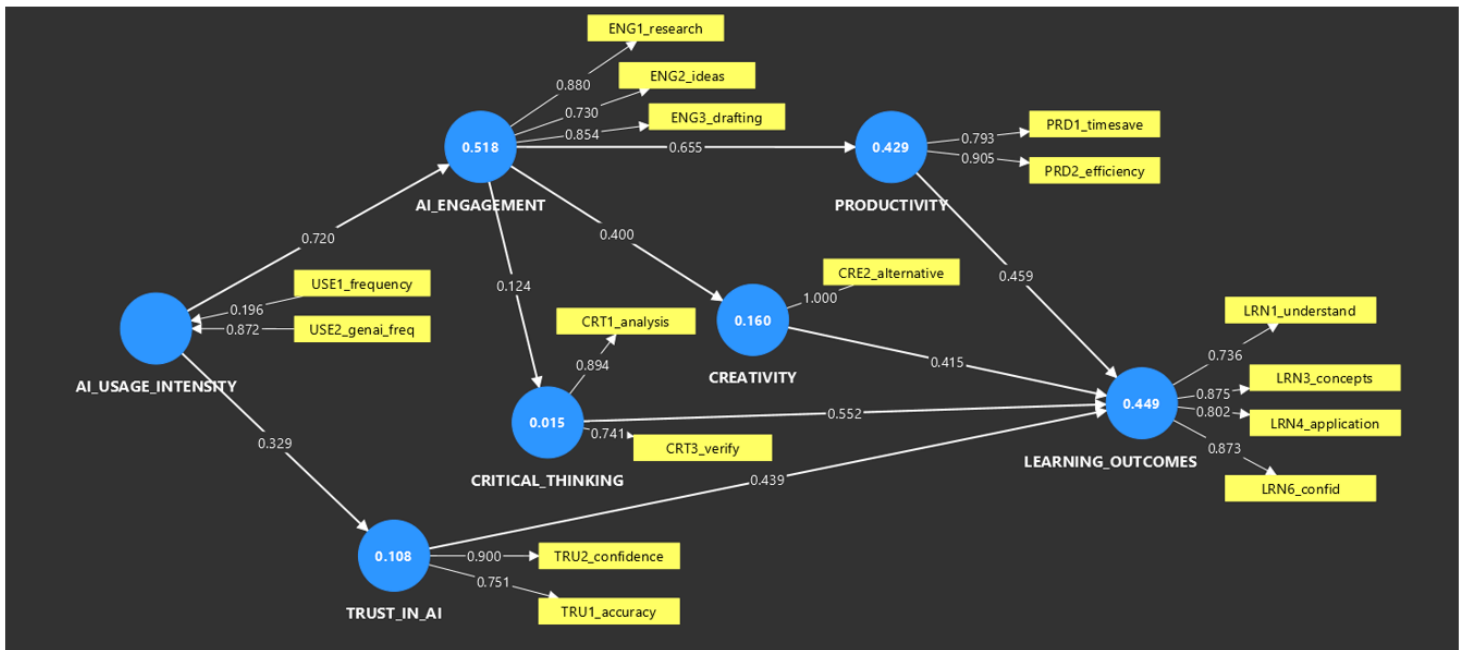


Figure 9

## Structural Model

Source: Author's calculations based on SmartPLS 4 output

## Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryMaterial.docx](#)