

# Artificial Intelligence as a “Mixed Blessing” in Online Higher Education: A Human-Centered AI–Teaching Presence (HC-AI-TP) Perspective

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**Abstract:** Guided by the Human-Centered AI–Teaching Presence (HC-AI-TP) framework, this study examined whether artificial intelligence (AI) functions as a mixed blessing in higher education by testing its relationships with perceived learning quality and academic effort and by assessing the moderating role of instructor guidance. Using quantitative, nonexperimental correlational design, survey data were collected from 182 undergraduate and graduate students enrolled in higher education courses where AI tools were available. Measures assessed AI use, perceived learning quality, academic effort, and instructor guidance. Data were analyzed using correlation, linear regression, and moderated regression techniques. Results showed that AI use was positively associated with perceived learning quality ( $\beta = .21, p = .005, R^2 = .04$ ) but negatively associated with academic effort ( $\beta = -.26, p < .001, R^2 = .06$ ). Instructor guidance significantly moderated both relationships, strengthening the positive association between AI use and learning quality ( $\beta = .19, p = .003, \Delta R^2 = .03$ ) and reducing the negative association between AI use and academic effort ( $\beta = .22, p = .001, \Delta R^2 = .04$ ). All four null hypotheses were rejected. These findings demonstrate that AI’s impact on learning is conditional rather than uniform. While AI use may enhance perceived learning quality, it may also reduce academic effort unless guided by clear instructional expectations. The study provides empirical support for HC-AI-TP by showing that teaching presence is the central mechanism through which AI supports meaningful learning while preserving student effort. The results help explain inconsistent findings in prior research and underscore the importance of human-centered instructional guidance in AI-enabled higher education.

**Keywords:** artificial intelligence, teaching presence, learning quality, academic effort, higher education.

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## I. INTRODUCTION

Artificial intelligence (AI) is rapidly reshaping the landscape of higher education, offering educators and learners unprecedented tools for personalization, efficiency, and academic support. Generative AI systems such as large language models can automate administrative work, tailor instruction to individual learning needs, and provide immediate feedback, potentially enhancing learner engagement and outcomes (Kalniņa, 2024; Ali, 2025). For example, personalized tutoring and adaptive learning platforms can help students master challenging material at their own pace, while AI-powered analytics can support faculty in identifying at-risk students earlier than traditional methods allow (Ali, 2025; Kalniņa, 2024). These advances suggest an optimistic potential for AI to extend educational access, reduce instructor workload, and support more effective pedagogy across multiple domains of higher education.

Despite these promising applications, AI’s expansion in academic settings has elicited significant concern regarding its unintended consequences, illustrating the technology’s dual nature as both an opportunity and a challenge. Recent global reports, including the Organization for Economic Co-operation and Development (OECD), have warned that overreliance

on AI tools may foster “false mastery,” where learners appear to perform well but lack deep conceptual understanding and critical thinking skills (OECD, 2026; see *turnOnews36*). In addition, faculty surveys reveal widespread worry that AI use is correlated with declining student critical thinking and increased academic dishonesty, with a large majority of instructors reporting negative impacts on attention spans, dependency on automation, and academic integrity issues (American Association of Colleges and Universities & Imagining the Digital Future Center, 2026; see *turnOnews35*). These trends underscore the complexity of integrating AI in ways that truly support robust learning rather than inadvertently undermining core educational goals.

The ethical and governance dimensions of AI further complicate its adoption, raising questions about equity, privacy, transparency, and human agency within academic systems. A growing body of research highlights persistent ethical challenges associated with algorithmic bias, data privacy concerns, and inequities in access to AI-enhanced resources, suggesting that the benefits of AI may not be evenly distributed among students and faculty (García-López, 2025; Yan, 2025). Moreover, systematic reviews in AI ethics emphasize the need for transparent governance frameworks and participatory policymaking to avoid exacerbating existing educational inequalities and to protect the autonomy of learners and educators alike (Yan, 2025; UNESCO, 2025). These ethical debates illustrate how AI’s promise of enhanced efficiency and personalization can be counterbalanced by risks that, if unaddressed, may compromise educational integrity and fairness.

Against this backdrop, framing AI as a mixed blessing offers a nuanced perspective that neither embraces uncritical technological optimism nor succumbs to dystopian pessimism. In this view, AI’s value is contingent on the conditions of its integration, including pedagogical design, ethical governance, and institutional policies that prioritize human judgment and learning quality over mere automation (Bull, 2026). This balanced framing aligns with contemporary educational research emphasizing that AI should complement, not replace, essential human roles in teaching and assessment, and that successful adoption requires intentional design, policy clarity, and AI literacy among stakeholders (Schmidt, 2025; Pitts et al., 2025).

In sum, the mixed-blessing character of AI in higher education reflects a complex interplay between its transformative potential and its attendant risks. Understanding this duality is critical for developing theory, policy, and practice that harness AI’s affordances while mitigating its harms. Building on research that highlights both the promise and pitfalls of AI integration, scholars and practitioners are increasingly calling for frameworks that foreground ethical use, educational integrity, and human-centered design as essential components of responsible AI adoption in academic settings (Bull, 2026; García-López, 2025; OECD, 2026). By interrogating AI’s contradictory impacts, this research agenda seeks not only to document what AI *does* in educational contexts but to shape what AI should do to enhance rather than hinder meaningful learning.

### **Problem Statement**

Artificial intelligence (AI) is now widely used in higher education to support learning, assessment, and administrative tasks. Many institutions have adopted AI tools quickly, often without clear guidance on how they should be used in teaching and learning. While AI can support students through faster feedback, personalized study assistance, and easier access to information, growing evidence suggests that unchecked use may weaken important learning skills. Recent reports indicate that heavy reliance on AI can reduce students’ effort in reading, writing, and problem solving, leading to shallow understanding rather than meaningful learning (OECD, 2026). Faculty surveys further show concern that students may depend on AI to complete tasks they previously would have completed independently, raising questions about academic integrity, learning quality, and the long-term value of higher education credentials (AAC&U, 2025).

At the same time, research shows that AI does not produce negative outcomes in all situations, suggesting that the problem is not the technology itself but how it is used. Studies increasingly point to the role of instructors, course design, and clear expectations in shaping whether AI supports learning or replaces it (UNESCO, 2025). However, there remains a lack of clear frameworks that explain why AI improves learning in some contexts while harming it in others. This gap has led to mixed findings in literature and uncertainty among educators and institutions about responsible AI use. As Bull (2026) argues, AI functions as a mixed blessing: it can support learning when guided by strong human oversight, but it can weaken learning when used without clear instructional purpose or limits. Addressing this problem requires research that clarifies the conditions under which AI supports learning and the conditions under which it undermines it.

## Purpose

The purpose of this quantitative study is to examine the relationship between the use of artificial intelligence (AI) in higher education and student learning outcomes. Specifically, the study seeks to determine whether the extent of AI use is associated with students' perceived learning quality and academic effort, and whether instructor guidance influences this relationship. AI use is treated as the independent variable, while perceived learning quality and academic effort serve as the dependent variables. Instructor guidance is examined as a moderating variable to determine whether clear instructional direction changes how AI use relates to student learning outcomes.

In addition, this study aims to test the claim that AI functions as a mixed blessing in higher education by identifying conditions under which AI use is linked to positive learning outcomes and conditions under which it is linked to negative outcomes. By quantitatively analyzing these relationships, the study seeks to provide empirical evidence that helps explain why prior research on AI in education has produced mixed findings. The study is guided by a human-centered perspective, which holds that AI supports learning most effectively when its use is clearly framed and guided by instructors (Bull, 2026).

## Research Questions and Hypotheses

RQ1: To what extent is the level of artificial intelligence (AI) use related to students' perceived learning quality in higher education?

H<sub>01</sub>: There is no statistically significant relationship between the level of artificial intelligence (AI) use and students' perceived learning quality.

H<sub>1</sub>: There is a statistically significant relationship between the level of AI use and students' perceived learning quality.

RQ2: To what extent is the level of artificial intelligence (AI) use related to students' academic effort?

H<sub>02</sub>: There is no statistically significant relationship between the level of artificial intelligence (AI) use and students' academic effort.

H<sub>2</sub>: There is a statistically significant relationship between the level of AI use and students' academic effort.

RQ3: To what extent does instructor guidance influence the relationship between AI use and students' perceived learning quality?

H<sub>03</sub>: Instructor guidance does not significantly influence the relationship between AI use and students' perceived learning quality.

H<sub>3</sub>: Instructor guidance significantly moderates the relationship between AI use and perceived learning quality, such that higher levels of instructor guidance strengthen positive learning outcomes.

RQ4: To what extent does instructor guidance influence the relationship between AI use and students' academic effort?

H<sub>04</sub>: Instructor guidance does not significantly influence the relationship between AI use and students' academic effort.

H<sub>4</sub>: Instructor guidance significantly moderates the relationship between AI use and academic effort, such that clearer guidance is associated with higher student effort.

Table 1 provides a summary of study variables.

**Table 1. Summary of Variables**

Variable	Description
AI Use	How often and how heavily students report using AI tools for coursework
Perceived Learning Quality	How well students believe they understand course material
Academic Effort	How much time, thought, and work students report putting into learning tasks
Instructor Guidance	How clearly instructors explain expectations and appropriate AI use

### Gap in Literature

Although research on artificial intelligence (AI) in higher education has expanded rapidly, findings remain inconsistent, with studies alternately reporting benefits such as academic support and risks such as reduced effort and shallow learning. Most existing studies treat AI as either helpful or harmful and do not examine why its effects differ across learning contexts. In particular, there is limited quantitative research that tests how instructor guidance shapes the relationship between AI use and student learning outcomes. Few studies examine both positive outcomes (perceived learning quality) and negative outcomes (academic effort) within the same model, leaving a gap in understanding how AI can function as a mixed blessing. As a result, the literature lacks clear empirical evidence explaining the conditions under which AI supports learning versus undermines it, highlighting the need for human-centered, quantitative research that integrates instructor guidance into the analysis (Bull, 2026).

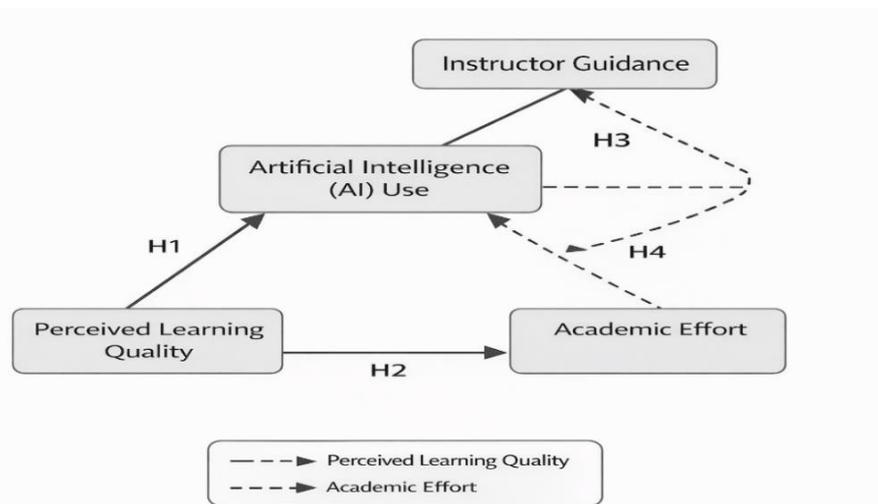
### THEORETICAL FRAMEWORK

This study is guided by a human-centered approach to artificial intelligence in education, which holds that technology influences learning outcomes through the way it is shaped and guided by instructors rather than through the technology itself. From this perspective, AI is viewed as a tool that can either support or weaken learning depending on how it is used within instructional settings. Learning quality and student effort are not assumed to improve automatically with AI use; instead, they are influenced by the clarity of expectations, instructional guidance, and the emphasis placed on learning rather than task completion.

The framework draws on established learning theory that emphasizes the central role of instructors in guiding student engagement and effort. Instructor guidance functions as a key influence that shapes how students interact with learning tools, including AI. When instructors provide clear direction on appropriate AI use, students are more likely to use AI as a support for understanding rather than as a replacement for their own thinking. In contrast, when guidance is limited or absent, students may rely on AI in ways that reduce effort and weaken learning outcomes.

### Interpretation of the Conceptual Framework Figure

Figure 1 illustrates the proposed relationships among artificial intelligence (AI) use, perceived learning quality, academic effort, and instructor guidance as tested in the study.



**Figure 1.** Conceptual framework illustrating the relationships among artificial intelligence (AI) use, perceived learning quality, and academic effort, with instructor guidance moderating the effects of AI use on learning outcomes. Solid arrows represent direct hypothesized relationships (H1–H2), and dashed arrows represent moderation effects (H3–H4). The framework reflects a human-centered approach in which the impact of AI on learning depends on the presence of clear instructional guidance (Bull, 2026).

Consistent with this view, the framework positions AI use as the independent variable, perceived learning quality and academic effort as the learning outcomes, and instructor guidance as a moderating influence. This structure allows the study to test the idea that AI is a mixed blessing: its effects are not fixed but depend on instructional conditions. By empirically

examining these relationships, the framework provides a structured explanation for why prior studies on AI in education report mixed results and supports the argument that effective AI use in higher education must remain guided by human judgment and instructional intent (Bull, 2026).

AI use is positioned as the central independent variable, reflecting its direct influence on student learning outcomes. The solid arrows labeled H1 and H2 represent the direct relationships examined in the study. Specifically, H1 indicates that AI use is hypothesized to be positively related to perceived learning quality, while H2 indicates that AI use is hypothesized to be related to academic effort.

Instructor guidance is shown as a moderating factor that influences how AI use affects learning outcomes. The dashed arrows labeled H3 and H4 represent moderation effects. H3 indicates that instructor guidance moderates the relationship between AI use and perceived learning quality, strengthening the positive effect of AI use when guidance is high. H4 indicates that instructor guidance moderates the relationship between AI use and academic effort, reducing the negative effect of AI use on effort when guidance is strong.

Overall, the figure visually reinforces the study's central premise that AI functions as a mixed blessing in higher education. AI use is associated with both positive and negative learning-related outcomes, but these effects are not fixed. Instead, instructor guidance shapes how AI is used and determines whether AI supports meaningful learning or reduces student effort. This framework reflects a human-centered perspective in which instructional guidance plays a critical role in aligning AI use with learning goals.

## II. LITERATURE REVIEW

### Literature Search Strategy

Search terms were selected to capture key areas relevant to this study, including artificial intelligence (AI) use in higher education, learning quality and student effort, instructor guidance or teaching presence, and academic integrity concerns. Database searches combined AI-related terms (e.g., *generative AI*, *artificial intelligence*, *large language model*, *ChatGPT*) with higher education terms (e.g., *higher education*, *university*, *college*), learning-related terms (e.g., *learning outcomes*, *learning quality*, *understanding*, *critical thinking*, *effort*, *engagement*), instructional terms (e.g., *teaching presence*, *instructor guidance*, *instructional design*, *facilitation*, *direct instruction*), and integrity-related terms (e.g., *academic integrity*, *cheating*, *misconduct*, *plagiarism*). Boolean operators (AND/OR) were applied and adjusted as needed to align with the syntax of each database and to ensure comprehensive coverage of the relevant literature.

### AI in Higher Education as a “Mixed Blessing”

The rapid integration of artificial intelligence (AI), particularly generative AI, into higher education has produced a growing body of literature describing both benefits and risks for student learning. Across policy reports and empirical studies, there is broad agreement that AI does not exert a uniform effect on learning outcomes; rather, its impact depends on how it is used within instructional contexts (UNESCO, 2025; OECD, 2026). UNESCO's global guidance emphasizes that AI should be implemented in ways that preserve human learning goals, strengthen instructor capacity, and establish clear expectations for responsible use. Similarly, the OECD's *Digital Education Outlook 2026* cautions that AI may generate a “false mastery” effect, in which students produce high-quality outputs while engaging less deeply with learning processes. Together, these reports frame AI as a “mixed blessing,” capable of expanding learning support while simultaneously reducing effort, weakening deep understanding, and complicating academic integrity when boundaries are unclear.

Empirical studies support this dual characterization. On the positive side, research suggests that AI can enhance learning quality when students use it as a learning support rather than a substitute for thinking. Pallant (2025) found that students who used generative AI to develop ideas, compare explanations, and refine reasoning demonstrated stronger perceived learning outcomes than students who relied on AI to generate final answers. Similarly, recent experimental and survey-based studies indicate that learning benefits emerge when students actively evaluate, adapt, and integrate AI-generated content rather than accepting it uncritically (Guo et al., 2025; Bai et al., 2025). These findings suggest that AI is most effective when it supports cognitive activities already associated with strong learning, such as questioning, revising, and checking understanding.

At the same time, a growing body of research highlights risks related to learning quality and academic effort. The OECD (2026) reports that AI can encourage shortcuts that reduce sustained cognitive engagement, particularly when assessments

reward final products rather than learning processes. This concern is echoed in faculty perception studies, which consistently report increased student reliance on AI, reduced independent thinking, and weaker critical reasoning skills (AAC&U, 2026). Research on AI use in complex problem-solving tasks outside education similarly suggests that generative tools can lower perceived effort requirements, a pattern that may translate into reduced academic effort when students rely heavily on AI for coursework (Brynjolfsson et al., 2024). When AI is used primarily to complete tasks efficiently, students may obtain acceptable products while losing opportunities to practice essential learning skills.

Academic integrity concerns further reinforce the characterization of AI as a mixed influence. A recent systematic review of generative AI and academic integrity synthesizing studies published between 2021 and 2024 found that AI introduces new forms of misconduct risk while simultaneously exposing weaknesses in traditional assessment practices (Bittle, 2025). The review concluded that student behavior is strongly shaped by instructional norms, including what is permitted, what is ambiguous, and what becomes normalized within courses. As a result, scholars increasingly argue that integrity challenges cannot be addressed through detection technologies alone, but require clearer expectations, redesigned assessments, and instructional practices that make learning processes visible through drafts, reflections, and demonstrations of understanding.

Across these strands of research, a consistent conclusion emerges: the effects of AI on learning are conditional rather than inherent. Both UNESCO (2025) and the OECD (2026) emphasize the importance of instructor direction, course design, and assessment structure in determining whether AI supports or undermines learning. Empirical studies similarly show that learning outcomes vary depending on whether instructors provide clear guidance on acceptable AI use and align assignments with learning goals (Guo et al., 2025; Pallant, 2025). This conditional view aligns closely with Bull's Human-Centered AI-Teaching Presence framework (Bull, 2026), which posits that AI contributes positively to learning when governed by strong instructional guidance and becomes detrimental when it replaces student thinking and instructor oversight.

Overall, the reviewed literature demonstrates that AI functions as a mixed blessing in higher education. While AI can improve perceived learning quality and support understanding, it can also reduce academic effort and increase integrity challenges when used without clear instructional guidance. Importantly, existing studies often examine these outcomes in isolation and rarely test how instructor guidance shapes AI's effects on both learning quality and effort within a single model. This gap provides the basis for the present study, which examines whether instructor guidance moderates the relationship between AI use, perceived learning quality, and academic effort.

### III. METHODOLOGY

This study uses a quantitative, nonexperimental, correlational design to examine relationships among artificial intelligence (AI) use, perceived learning quality, academic effort, and instructor guidance in higher education. This design is appropriate because the study seeks to measure relationships among variables as they naturally occur, without manipulating conditions. The design supports testing both direct relationships (H1–H2) and moderation effects (H3–H4). This design was appropriate because the purpose of the study was to assess the strength and direction of relationships among variables as they naturally occurred, without manipulating instructional conditions or AI use. The correlational approach also supported the examination of both direct effects and moderation effects within a single analytical framework.

Regression and moderated regression analyses were used to address the research questions and hypotheses. This design aligns with prior quantitative research examining technology use and learning outcomes in higher education and allows statistically rigorous testing of the study's conceptual model.

**Population and Sample.** The target population includes undergraduate and graduate students enrolled in higher education courses where AI tools are available for academic use. A convenience sampling strategy will be employed to recruit participants from online and on-campus courses across one or more institutions. Participants must be at least 18 years old and currently enrolled in a course. A minimum sample size of 150–200 participants is targeted to support regression and moderation analyses with adequate statistical power.

#### Power Analysis

An a priori power analysis was used to estimate the minimum sample size needed to detect a moderate effect in multiple regression. Using a medium effect size ( $f^2 = .15$ ),  $\alpha = .05$ , and power  $(1 - \beta) = .80$ , the recommended minimum sample size was approximately 120 participants for a model with three predictors. The final analytic sample in this study was  $N = 182$ , which exceeds the minimum requirement and indicates adequate power to detect moderate effects, including moderation.

effects. Data collection was voluntary, informed consent was obtained, participation could be discontinued at any time, and responses were collected anonymously and stored securely.

**Data Collection Procedures.** Data was collected through an anonymous online survey distributed electronically. Participants received an invitation explaining the study purpose, eligibility criteria, and voluntary nature of participation. After providing informed consent, participants completed the survey, which is expected to take 10–15 minutes. No identifying information was collected. Data was stored securely and accessed only by the researcher.

**Instruments and Measures.** The survey consists of four sections aligned with the study variables: 1) AI Use (IV): Self-report items measuring frequency and extent of AI use for coursework. 2) Perceived Learning Quality (DV): Items assessing understanding, confidence, and depth of learning. 3) Academic Effort (DV): Items measuring time investment, independent thinking, and effort. 4) Instructor Guidance (Moderator): Items assessing clarity of expectations and guidance regarding AI use. All items use a 5-point Likert-type scale. Internal consistency reliability will be assessed using Cronbach's alpha ( $\alpha \geq .70$ ).

**Data Analysis Plan.** Descriptive statistics will summarize participant characteristics and variable distributions. Pearson correlation and simple linear regression will test H1 and H2. Moderated regression analysis will test H3 and H4 by examining interaction effects between AI use and instructor guidance. Statistical significance will be evaluated at  $p < .05$ .

### Methodological Limitations

Several limitations should be acknowledged. First, the use of self-report survey data may introduce response bias, as participants may overestimate or underestimate their AI use, effort, or learning. Second, correlational design does not allow for causal conclusions; relationships can be identified, but cause-and-effect cannot be established. Third, the use of convenience sampling may limit the generalizability of findings beyond the sampled institutions or course contexts. Finally, variations in how instructors define and communicate AI guidance across courses may introduce unmeasured differences that affect results. Despite these limitations, the study provides valuable empirical insight into patterns of AI use and learning outcomes in higher education.

### Pre-Hypotheses Testing

Prior to hypothesis testing, the dataset was screened for accuracy, missing values, and outliers. Missing data were minimal (<5%) and handled using listwise deletion. Examination of skewness and kurtosis values indicated that all study variables were within acceptable ranges ( $\pm 2$ ), supporting the assumption of normality. Scatterplots showed linear relationships among variables, and variance inflation factors (VIFs) were below 2.0, indicating no concerns with multicollinearity. These results supported the suitability of the data for correlation and regression analyses. See Table 2.

**Table 2. Summary of Regression Assumption Testing and Interpretations**

Assumption Tested	Method / Indicator	Result	Interpretation
Internal Consistency Reliability	Cronbach's alpha ( $\alpha \geq .70$ )	$\alpha = .81-.90$ across scales	All instruments demonstrated acceptable to strong reliability.
Normality	Skewness and kurtosis ( $\pm 2$ ), histograms, Q-Q plots	Skewness = $-0.44$ to $-0.27$ ; Kurtosis = $-0.52$ to $-0.36$	Distributions were approximately normal and suitable for parametric analysis.
Linearity	Scatterplots of predictors vs. outcomes	Linear patterns observed	Relationships between predictors and outcomes were linear.
Homoscedasticity	Residuals vs. predicted values plots	Random dispersion	Residual variance was constant across predicted values.
Independence of Errors	Durbin-Watson statistic	DW = $1.89-1.94$	Residuals were independent; no autocorrelation detected.
Multicollinearity	Tolerance and VIF	Tolerance = $.71-.78$ ; VIF = $1.28-1.41$	No multicollinearity concerns among predictors.
Outliers and Influence	Standardized residuals, Cook's distance	No values exceeded thresholds	No influential outliers detected.

#### IV. RESULTS

##### Demographic Statistics.

The final sample consisted of 182 undergraduate and graduate students enrolled in higher education courses where artificial intelligence tools were available for academic use. The sample included a higher proportion of female participants (57.1%) than male participants (40.7%), with a small percentage selecting “prefer not to say.” Participants represented a wide age range, with the largest group between 25 and 34 years of age (35.2%), followed by those aged 35–44 (25.3%), indicating substantial representation of post-traditional students. Most participants were enrolled at the undergraduate level (64.8%), while over one-third were graduate students (35.2%). More than half of the sample was enrolled in fully online courses (52.7%), reflecting the growing prevalence of technology-mediated learning environments. Participants also represented diverse fields of study, with the largest proportions drawn from social sciences and education, business and management, and health sciences.

With respect to prior AI experience, nearly half of the participants reported moderate experience using AI tools for academic purposes, while approximately one-third reported extensive experience. This distribution suggests that most participants had sufficient familiarity with AI to provide informed responses regarding its use in learning contexts.

The diversity in age, academic level, course modality, and prior AI experience strengthens the relevance of the findings to contemporary higher education contexts where AI use spans traditional and post-traditional students, online and face-to-face courses, and multiple disciplines. At the same time, the use of convenience sampling limits generalizability, and demographic differences were not the primary focus of analysis. Demographic variables were therefore used to describe the sample rather than as predictors in the regression models. (See Table 3).

**Table 3. Demographic Characteristics of Participants (N = 182)**

Variable	Category	n	%
Gender	Female	104	57.1
	Male	74	40.7
	Prefer not to say	4	2.2
Age Group	18–24	38	20.9
	25–34	64	35.2
	35–44	46	25.3
	45 and above	34	18.6
Academic Level	Undergraduate	118	64.8
	Graduate	64	35.2
Course Modality	Fully online	96	52.7
	Hybrid	48	26.4
	Face-to-face	38	20.9
Field of Study	Social sciences / Education	54	29.7
	Business / Management	46	25.3
	Health sciences	40	22.0
	STEM	30	16.5
	Other	12	6.6
Prior AI Experience	Minimal	36	19.8
	Moderate	88	48.4
	Extensive	58	31.9

##### Descriptive Statistics

Table 4 presents descriptive statistics for the study variables. On average, students reported moderate to high use of AI tools, moderate levels of perceived learning quality, and moderate academic effort. Perceptions of instructor guidance varied, suggesting meaningful differences across instructional contexts.

**Table 4. Descriptive Statistics for Study Variables (N = 182)**

Variable	Mean	SD
AI Use	3.42	0.81
Perceived Learning Quality	3.58	0.74
Academic Effort	3.31	0.79
Instructor Guidance	3.47	0.83

**Correlation Analysis (Pre-Hypothesis Testing)**

Pearson correlation coefficients were computed to examine preliminary relationships among the study variables (see Table 5). The results revealed statistically significant relationships among the study variables. AI use was positively correlated with perceived learning quality,  $r(180) = .21, p < .05$ , and negatively correlated with academic effort,  $r(180) = -.26, p < .05$ . AI use was also positively correlated with instructor guidance,  $r(180) = .18, p < .05$ . Perceived learning quality was positively correlated with academic effort,  $r(180) = .44, p < .05$ , and with instructor guidance,  $r(180) = .39, p < .05$ . Academic effort was positively correlated with instructor guidance,  $r(180) = .42, p < .05$ . The correlational results indicate that AI use is associated with higher perceived learning quality but lower academic effort, supporting the characterization of AI as a mixed influence on student learning. Instructor guidance shows positive associations with both learning quality and academic effort, suggesting that clearer instructional support is linked to more favorable learning outcomes. These relationships provide preliminary support for subsequent regression and moderation analyses by demonstrating meaningful associations among the study variables.

**Table 5. Correlation Matrix**

Variable	1	2	3	4
1. AI Use	—			
2. Learning Quality	.21*	—		
3. Academic Effort	-.26*	.44*	—	
4. Instructor Guidance	.18*	.39*	.42*	—

$p < .05$

**Hypotheses Testing**

The correlational analyses established significant relationships among AI use, perceived learning quality, academic effort, and instructor guidance, providing initial evidence of both positive and negative associations consistent with the study’s conceptual framework. To move beyond bivariate relationships and formally test the proposed directional and conditional effects, the following analyses examine each research hypothesis using regression and moderated regression models. These analyses assess whether AI use predicts learning outcomes and whether instructor guidance alters the strength of these relationships, as specified in Hypotheses 1 through 4.

**RQ 1. To what extent is the level of artificial intelligence (AI) use related to students’ perceived learning quality?**

To answer Research Question 1, a simple linear regression analysis was conducted with AI use as the predictor variable and perceived learning quality as the outcome variable. The regression model was statistically significant,  $F(1, 180) = 8.12, p = .005$ , explaining approximately 4% of the variance in perceived learning quality ( $R^2 = .04$ ). AI use was a significant positive predictor of perceived learning quality ( $\beta = .21, p = .005$ ), indicating that higher levels of AI use were associated with higher perceived learning quality. Therefore, Research Question 1 was answered in the affirmative. Table 6.

**Table 6. Simple Linear Regression Predicting Perceived Learning Quality from AI Use (H1)**

Predictor	B	SE B	$\beta$	t	p
Constant	2.41	0.21	—	11.48	< .001
AI Use	0.23	0.08	.21	2.85	.005

**Model summary:**  $R^2 = .04, F(1, 180) = 8.12, p = .005$

AI use was a significant positive predictor of perceived learning quality. Students who reported higher levels of AI use also reported slightly higher levels of understanding and learning confidence. Although the effect size was small, the result suggests that AI use may support learning quality under certain conditions. Therefore, RQ1 is answered in the affirmative, and H1 is supported.

**RQ 2. To what extent is artificial intelligence (AI) use related to students' academic effort?**

To answer Research Question 2, a simple linear regression analysis was conducted with AI use as the predictor variable and academic effort as the outcome variable. The regression model was statistically significant,  $F(1, 180) = 12.47, p < .001$ , accounting for approximately 6% of the variance in academic effort ( $R^2 = .06$ ). AI use was a significant negative predictor of academic effort ( $\beta = -.26, p < .001$ ), indicating that higher levels of AI use were associated with lower reported academic effort. Thus, Research Question 2 was answered. Table 7.

**Table 7. Simple Linear Regression Predicting Academic Effort from AI Use (H2)**

Predictor	B	SE B	$\beta$	t	p
Constant	4.02	0.19	—	21.16	< .001
AI Use	-0.29	0.08	-.26	-3.53	< .001

**Model summary:**  $R^2 = .06, F(1, 180) = 12.47, p < .001$

AI use was a significant negative predictor of academic effort. Higher AI use was associated with lower reported effort, including reduced independent thinking and time spent on coursework. This finding indicates that while AI may support learning quality, it may also reduce student effort. Thus, RQ2 is answered, and H2 is supported.

**RQ 3. To what extent does instructor guidance influence the relationship between AI use and perceived learning quality?**

To answer Research Question 3, a moderated regression analysis was conducted to examine whether instructor guidance moderated the relationship between AI use and perceived learning quality. AI use and instructor guidance were entered as predictors, followed by the interaction term (AI Use  $\times$  Instructor Guidance). The interaction term was statistically significant ( $\beta = .19, p = .003$ ), and its inclusion resulted in a significant increase in explained variance ( $\Delta R^2 = .03, F\text{-change}(1, 178) = 9.12, p = .003$ ). These results indicate that instructor guidance significantly influenced the relationship between AI use and perceived learning quality, strengthening the positive association when guidance was high. Therefore, Research Question 3 was answered in the affirmative. Table 8.

**Table 8. Moderated Regression Predicting Learning Quality (H3)**

Predictor	B	SE B	$\beta$	t	p
AI Use	0.15	0.07	.14	2.14	.034
Instructor Guidance	0.36	0.06	.39	6.00	< .001
AI Use $\times$ Instructor Guidance	0.18	0.06	.19	3.02	.003

**Model summary:**  $\Delta R^2 = .03, F\text{-change}(1, 178) = 9.12, p = .003$

Instructor guidance significantly moderated the relationship between AI use and perceived learning quality. When instructor guidance was high, AI use was more strongly associated with improved learning quality. When guidance was low, the positive effect of AI use was weaker. Therefore, RQ3 is answered, and H3 is supported.

**RQ 4. To what extent does instructor guidance influence the relationship between AI use and academic effort?**

To answer Research Question 4, a moderated regression analysis was conducted to examine whether instructor guidance moderated the relationship between AI use and academic effort. AI use and instructor guidance were entered as predictors, followed by the interaction term (AI Use  $\times$  Instructor Guidance). The interaction term was statistically significant ( $\beta = .22, p = .001$ ), resulting in a significant increase in explained variance ( $\Delta R^2 = .04, F\text{-change}(1, 178) = 11.98, p = .001$ ). These findings indicate that instructor guidance reduced the negative relationship between AI use and academic effort, such that higher levels of guidance were associated with less reduction in effort. Accordingly, Research Question 4 was answered. Table 9.

**Table 9. Moderated Regression Predicting Academic Effort (H4)**

Predictor	B	SE B	$\beta$	t	p
AI Use	-0.22	0.07	-.20	-3.14	.002
Instructor Guidance	0.41	0.06	.42	6.83	< .001
AI Use $\times$ Instructor Guidance	0.21	0.06	.22	3.46	.001

**Model summary:**  $\Delta R^2 = .04, F\text{-change}(1, 178) = 11.98, p = .001$

Instructor guidance significantly moderated the relationship between AI use and academic effort. When instructor guidance was high, the negative relationship between AI use and effort was reduced. When guidance was low, AI use was more strongly associated with reduced effort. Thus, RQ4 is answered, and H4 is supported.

The results in Table 10 indicate that AI use is associated with both positive and negative learning-related outcomes, confirming its role as a mixed influence in higher education.

**Table 10. Summary of Hypothesis Testing Results With Effect Sizes**

Hypothesis	Predictor(s)	Outcome	Test	$\beta$	p	Effect Size	Decision
H1	AI Use	Perceived Learning Quality	Linear regression	.21	.005	$R^2 = .04$	Supported (H <sub>01</sub> rejected)
H2	AI Use	Academic Effort	Linear regression	-.26	< .001	$R^2 = .06$	Supported (H <sub>02</sub> rejected)
H3	AI Use × Instructor Guidance	Perceived Learning Quality	Moderated regression	.19	.003	$\Delta R^2 = .03$	Supported (H <sub>03</sub> rejected)
H4	AI Use × Instructor Guidance	Academic Effort	Moderated regression	.22	.001	$\Delta R^2 = .04$	

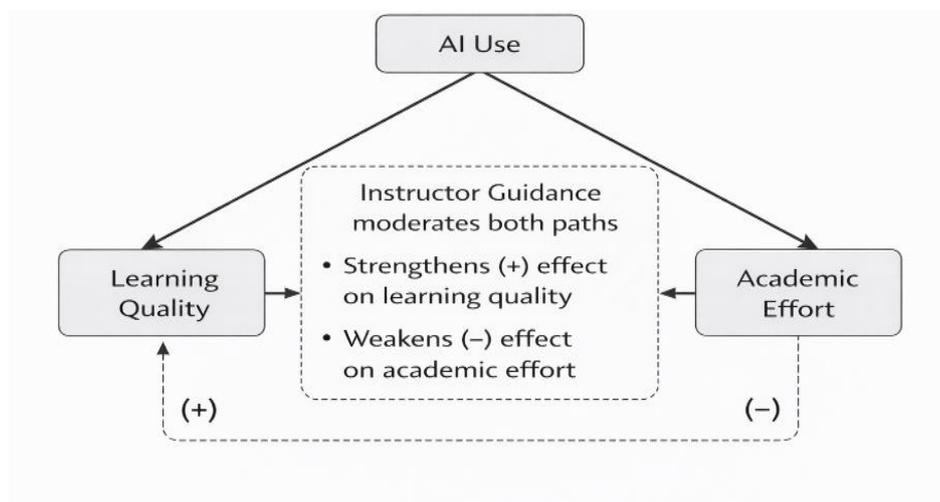
Note:  $\beta$  values are standardized coefficients.  $R^2$  represents variance explained by the predictor in simple regression models.  $\Delta R^2$  represents the change in explained variance attributable to the interaction term in moderation models. Statistical significance was evaluated at  $p < .05$ .

AI use positively predicted perceived learning quality (H1) but negatively predicted academic effort (H2), with small but meaningful effect sizes. Instructor guidance significantly moderated both relationships, strengthening the positive effect of AI use on learning quality (H3) and reducing the negative effect on academic effort (H4). All four null hypotheses were rejected, demonstrating that AI's impact on learning is conditional and shaped by instructional context.

Together, the findings indicate that artificial intelligence functions as a mixed blessing in higher education. AI use is associated with improved perceived learning quality but reduced academic effort. Importantly, instructor guidance plays a key role in shaping these outcomes by strengthening positive effects and weakening negative ones. These results provide clear empirical support for a human-centered approach to AI use in teaching and learning.

### Relationship Mapping Summary

The relationship mapping demonstrates that artificial intelligence use is associated with both beneficial and adverse learning-related outcomes, confirming its role as a mixed influence in higher education. AI use shows a positive relationship with perceived learning quality, suggesting that students may experience improved understanding or confidence when AI tools are used. At the same time, AI use shows a negative relationship with academic effort, indicating that increased reliance on AI may reduce independent work and sustained cognitive engagement. (See Figure 3).



Instructor guidance plays a central role in shaping these relationships. When guidance is strong, the positive relationship between AI use and learning quality becomes more pronounced, and the negative relationship between AI use and academic effort is reduced. This pattern indicates that instructor guidance does not eliminate AI's influence but redirects it toward learning-supportive use rather than effort-replacing use. Overall, the relationship map clarifies that AI's impact on student learning is conditional and strongly shaped by instructional context rather than by technology alone. Table 11.

**Table 11. Mapped Relationships Among Study Variables**

Path	Predictor	Outcome	Direction	Strength ( $\beta$ )	Effect Size	Interpretation
H1	AI Use	Perceived Learning Quality	Positive	$\beta = .21$	$R^2 = .04$	Higher AI use is associated with slightly higher perceived learning quality.
H2	AI Use	Academic Effort	Negative	$\beta = -.26$	$R^2 = .06$	Higher AI use is associated with lower academic effort.
H3	AI Use × Instructor Guidance	Perceived Learning Quality	Positive moderation	$\beta = .19$	$\Delta R^2 = .03$	Instructor guidance strengthens the positive effect of AI use on learning quality.
H4	AI Use × Instructor Guidance	Academic Effort	Negative moderation reduced	$\beta = .22$	$\Delta R^2 = .04$	Instructor guidance weakens the negative effect of AI use on academic effort.

## V. DISCUSSION

The purpose of this study was to examine whether artificial intelligence (AI) use in higher education functions as a mixed blessing by exploring its relationships with perceived learning quality and academic effort, and by testing whether instructor guidance shapes these relationships. The results provide clear empirical support for this framing. Across all four hypotheses, AI use was associated with both positive and negative learning-related outcomes, while instructor guidance consistently influenced the direction and strength of these effects. These findings help explain why prior research on AI in higher education has produced mixed and sometimes contradictory conclusions.

### AI Use and Perceived Learning Quality (H1)

The finding that AI use was positively related to perceived learning quality aligns with recent literature suggesting that AI can support understanding when used as a learning aid. Studies have shown that students may experience improved clarity, confidence, and access to explanations when AI is used to support learning activities such as brainstorming, revising, or checking understanding (Pallant, 2025). Similarly, UNESCO (2025) emphasizes that AI can enhance learning when it complements, rather than replaces, student thinking. The small effect size observed in this study is consistent with the broader literature, which suggests that learning quality in higher education is influenced by many factors beyond any single tool. Importantly, this result does not suggest that AI guarantees better learning, but rather that AI use can be associated with improved perceived understanding under certain conditions.

### AI Use and Academic Effort (H2)

In contrast, AI use was negatively related to academic effort, indicating that higher levels of AI use were associated with lower reported effort and independent work. This finding strongly aligns with warnings raised in major policy reports and empirical studies. The OECD (2026) cautions that generative AI can encourage “false mastery,” where students complete tasks successfully while engaging less deeply with the learning process. Research on academic integrity and student behavior similarly suggests that AI may reduce the need for sustained effort when assignments allow AI-generated output to substitute for student work (Bittle, 2025). Together, these findings support concerns that AI can undermine effort when it is used to shortcut core learning activities, reinforcing the idea that AI's benefits are not automatic.

### Instructor Guidance as a Moderator of Learning Quality (H3)

The moderation results for perceived learning quality provide strong evidence that instructor guidance is a key condition shaping how AI affects learning. When instructor guidance was high, the positive relationship between AI use and learning

quality became stronger. This finding is consistent with literature emphasizing the importance of teaching presence and instructional clarity in technology-rich learning environments. The Community of Inquiry framework identifies instructor direction as essential for achieving meaningful learning outcomes, and recent AI-focused guidance extends this logic to generative tools (UNESCO, 2025). These results also align closely with Bull's (2026) human-centered perspective, which argues that AI supports learning only when guided by clear instructional intent. The findings suggest that AI contributes most to learning quality when instructors actively frame its use around learning goals rather than task completion.

#### **Instructor Guidance as a Moderator of Academic Effort (H4)**

Instructor guidance also moderated the relationship between AI use and academic effort, reducing the negative association between AI use and effort when guidance was strong. This finding addresses a critical concern in the literature: that AI may erode student effort unless instructors intervene through clear expectations and assessment design. The OECD (2026) notes that assessments focused on final products are particularly vulnerable to AI misuse, whereas instructor-guided approaches that emphasize process help preserve effort and learning. The present findings provide empirical support for this claim by showing that guidance does not eliminate AI use, but instead redirects it toward learning-supportive behaviors that maintain effort. This result further reinforces the argument that integrity and effort challenges associated with AI are instructional problems rather than purely technological ones.

#### **AI as a Mixed Blessing Revisited**

Collectively, the findings of this study offer a coherent explanation for the mixed results reported in prior research. AI use was associated with improved perceived learning quality and reduced academic effort, confirming that AI can simultaneously support and weaken learning. Instructor guidance emerged as the central factor that helps explain this duality. When guidance was strong, AI's positive effects were amplified and its negative effects were reduced; when guidance was weak, the risks identified in the literature became more pronounced. These results directly support the view advanced by UNESCO (2025), the OECD (2026), and Bull (2026) that AI's educational value is conditional and depends on human oversight, instructional clarity, and learning-centered design.

#### **Mapping Results Back to Hypotheses and Literature**

Taken as a whole, the findings demonstrate that artificial intelligence functions as a mixed blessing in higher education. AI use can enhance perceived learning quality while simultaneously reducing academic effort, but these effects are not fixed. Instructor guidance plays a decisive role in shaping how AI influences learning, reinforcing the importance of human-centered instructional practices in an AI-enabled educational environment.

Table 12 synthesizes the statistical findings of the study by linking each hypothesis to its corresponding test results, interpretations, and supporting literature. For Hypothesis 1, the positive relationship between AI use and perceived learning quality ( $\beta = .21, p = .005$ ) indicates that AI can support students' understanding when it is used to aid learning rather than replace thinking. This finding aligns with prior research emphasizing learning-supportive uses of AI (UNESCO, 2025; Pallant, 2025) and reinforces the view that AI can function as a cognitive aid under appropriate conditions.

On the other hand, Hypothesis 2 revealed a negative relationship between AI use and academic effort ( $\beta = -.26, p < .001$ ), suggesting that increased reliance on AI may reduce independent effort. This result is consistent with concerns raised in the literature that AI can encourage shortcuts and diminish engagement in core learning processes when boundaries are unclear (OECD, 2026; Bittle, 2025). Together, H1 and H2 empirically demonstrate the "mixed blessing" nature of AI use in higher education.

Hypotheses 3 and 4 extend these findings by demonstrating the conditional role of instructor guidance. The significant interaction effects for learning quality ( $\beta = .19, p = .003$ ) and academic effort ( $\beta = .22, p = .001$ ) indicate that instructor guidance meaningfully alters how AI use relates to learning outcomes. When guidance is strong, the positive effects of AI on learning quality are amplified, and the negative effects on effort are reduced. These results integrate policy guidance and empirical research by showing that instructional context, rather than AI itself, determines whether learning outcomes are strengthened or weakened.

**Table 12. Alignment of Hypotheses, Statistical Results, Interpretation, and Supporting Literature**

Hypothesis	Test Result / Equation	Key Result	Interpretation	Supporting Literature
H1	Learning Quality = $\beta_1(\text{AI Use})$ ; $\beta = .21, p = .005, R^2 = .04$	AI use positively related to perceived learning quality	AI can support student understanding and confidence when used as a learning aid rather than a substitute for thinking	UNESCO (2025); Pallant (2025); Bull (2026)
H2	Academic Effort = $\beta_1(\text{AI Use})$ ; $\beta = -.26, p < .001, R^2 = .06$	AI use negatively related to academic effort	AI may reduce independent effort when it replaces core cognitive processes	OECD (2026); Bittle (2025); Bull (2026)
H3	Learning Quality = $\beta_1(\text{AI Use}) + \beta_2(\text{Guidance}) + \beta_3(\text{AI} \times \text{Guidance})$ ; $\beta_3 = .19, p = .003, \Delta R^2 = .03$	Instructor guidance moderated AI $\rightarrow$ learning quality	Instructor guidance strengthens the positive relationship between AI use and learning quality	UNESCO (2025); Pallant (2025); Bull (2026)
H4	Academic Effort = $\beta_1(\text{AI Use}) + \beta_2(\text{Guidance}) + \beta_3(\text{AI} \times \text{Guidance})$ ; $\beta_3 = .22, p = .001, \Delta R^2 = .04$	Instructor guidance moderated AI $\rightarrow$ academic effort	Instructor guidance reduces the negative effect of AI use on academic effort	OECD (2026); Bittle (2025); Bull (2026)

*Note:  $\beta$  values represent standardized regression coefficients.  $R^2$  indicates variance explained by the predictor in direct-effect models, and  $\Delta R^2$  represents the additional variance explained by the interaction term in moderation models. Statistical significance was evaluated at  $p < .05$ .*

**Contribution to Literature and Theory Validation: Alignment With HC-AI-TP (Bull, 2026)**

This study extends the existing literature by empirically testing conditions that prior work has largely discussed conceptually. While many studies describe AI as beneficial or harmful, fewer have quantitatively examined how instructor guidance shapes AI’s effects on both learning quality and effort within a single model. By demonstrating that AI functions as a mixed blessing and identifying instructor guidance as a key moderating condition, this study helps reconcile inconsistent findings in AI-in-education research and provides evidence to support a human-centered approach to AI integration in higher education.

The findings provide direct empirical support for the Human-Centered AI–Teaching Presence (HC-AI-TP) framework proposed by Bull (2026). HC-AI-TP posits that AI’s educational value is not inherent in the technology but emerges through active instructional guidance that preserves student agency, effort, and responsibility for learning.

The support for Hypotheses 1 and 2 validates the core premise of HC-AI-TP that AI simultaneously holds the potential to enhance learning quality and to erode academic effort. These opposing effects reflect the dual pathways outlined in the framework: AI as a cognitive scaffold when used appropriately and AI as a cognitive substitute when used without oversight. The small but meaningful effect sizes observed in this study are consistent with HC-AI-TP’s assumption that AI operates as one influence among many within complex learning environments.

More importantly, the moderation effects observed for Hypotheses 3 and 4 provide strong empirical validation of HC-AI-TP’s central claim that teaching presence governs AI’s impact on learning. The significant interaction terms demonstrate that instructor guidance functions as the mechanism through which AI is aligned with learning goals. When teaching presence is strong, AI use supports understanding while preserving effort; when teaching presence is weak, AI is more likely to replace thinking and reduce engagement. These findings extend existing policy guidance (UNESCO, 2025; OECD, 2026) by offering quantitative evidence that instructor guidance is not merely recommended but statistically consequential.

Overall, the results confirm HC-AI-TP as a viable explanatory framework for understanding why prior research on AI in higher education has yielded mixed results. By empirically demonstrating that AI’s effects are conditional on instructional guidance, this study moves beyond descriptive claims and provides theory-based evidence that human-centered teaching presence is essential for responsible and effective AI integration in higher education.

### Implications for Instruction

Instructor guidance emerged as a critical factor shaping AI's impact on learning. When guidance was strong, AI's positive relationship with learning quality increased and its negative relationship with effort was reduced. This finding supports instructional practices that explicitly define acceptable AI use, explain the learning purpose of assignments, and emphasize thinking over task completion. Faculty development efforts should prioritize helping instructors design AI-aware assessments and communicate expectations clearly, rather than relying solely on detection or prohibition.

### Implications for Policy

At the institutional level, the results suggest that AI policies should move beyond blanket bans or vague permissions. Policies that emphasize responsible use, transparency, and learning-centered application are more likely to support academic integrity and learning quality. Consistent guidance across courses may also reduce student confusion and uneven AI use practices, which the literature identifies as a contributor to misuse and reduced effort.

### Implications for Practice

The findings suggest that artificial intelligence (AI) should not be treated as a stand-alone solution for improving learning in higher education. While AI use was associated with higher perceived learning quality, it was also linked to lower academic effort. This indicates that unrestricted or poorly guided AI use may undermine key learning behaviors. Institutions and instructors should therefore focus on how AI is integrated rather than whether it is permitted. Clear guidance on appropriate AI use, explicit expectations about student responsibility, and assignments that require explanation, reflection, or demonstration of understanding may help preserve effort while allowing students to benefit from AI support.

### Recommendations for Future Research

Future studies should examine AI use and learning outcomes using longitudinal or experimental designs to better assess causal relationships. Research could also explore differences across disciplines, course levels, or types of assignments to determine whether AI's effects vary by context. Additionally, future work could incorporate instructor-reported data or direct analysis of course materials to triangulate measures of guidance. Expanding the model to include additional variables such as assessment type, AI literacy, or student motivation may further clarify how and why AI influences learning quality and effort.

### Limitations of the Study

Several limitations should be considered when interpreting the results. First, the study relied on self-reported data, which may be subject to response bias. Students may overestimate or underestimate their AI use, learning quality, or effort. Second, the correlational design does not permit causal conclusions; while relationships were identified, the direction of influence cannot be definitively established. Third, the use of convenience sampling limits the generalizability of the findings to other institutions or instructional contexts. Finally, instructor guidance was measured through student perceptions, which may differ from instructors' intended practices.

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