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Ethical Use of Artificial Intelligence and Cognitive Presence in Online Learning: A Human-Centered AI–Teaching Presence (HC-AI-TP) Perspective

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Abstract: **The rapid integration of artificial intelligence (AI) into online higher education has produced conflicting evidence regarding its impact on higher-order learning. Guided by the Community of Inquiry (CoI) framework and Human-Centered AI–Teaching Presence (HC-AI-TP) theory, this study examined whether the effects of AI-supported instruction on cognitive presence and perceived learning are conditional on teaching presence. Using a cross-sectional quantitative design, survey data were collected from 200 students enrolled in fully online courses. Previously validated instruments were employed, including the Human-Centered AI–Teaching Presence (HC-AI-TP) scale for AI-supported instruction, the CoI Teaching Presence and Cognitive Presence scales, and a validated perceived learning measure. Internal consistency reliability for all instruments was re-established in the present sample prior to hypothesis testing. Pearson correlation analyses indicated strong positive associations among teaching presence, cognitive presence, and perceived learning ($r = .55–.68$, $p < .001$), while AI-supported instruction demonstrated a modest bivariate association with cognitive presence ($r = .29$, $p < .001$). Regression analyses showed that AI-supported instruction did not independently predict cognitive presence ($\beta = .07$, $p = .170$), whereas teaching presence was a strong positive predictor ($\beta = .49$, $p < .001$). Moderation analysis revealed a significant AI × Teaching Presence interaction ($\beta = .21$, $p < .001$), indicating that AI enhanced cognitive presence only under conditions of strong teaching presence. In contexts of low teaching presence, AI use was associated with diminished cognitive engagement. Mediation analysis further demonstrated that cognitive presence fully mediated the relationship between ethical AI use—operationalized as AI-supported instruction governed by high teaching presence—and perceived learning (indirect effect = .34, 95% CI [.25, .45]). Phase-level analyses showed that the moderating effect of teaching presence was strongest for the integration ($\beta = .27$, $p < .001$) and resolution ($\beta = .31$, $p < .001$) phases of cognitive presence. Demographic variables were non-significant, and robustness checks confirmed the stability of the findings. Overall, the results indicate that AI is neither inherently beneficial nor harmful; its educational value depends on instructional governance through teaching presence. The study advances Bull's (2026) (HC-AI-TP) theory by positioning cognitive presence as an ethical learning outcome and provides empirical guidance for responsible AI integration in online higher education.**

Keywords: **artificial intelligence in education; teaching presence; cognitive presence; Community of Inquiry; ethical AI; online learning.**

I. INTRODUCTION

The rapid integration of artificial intelligence (AI) into higher education has generated both promise and concern regarding its pedagogical impact (Noroozi et al., 2025). AI-enabled tools are increasingly used to personalize instruction, automate routine tasks, and provide on-demand support for learners, leading many educators and researchers to describe AI as a transformative force in teaching and learning environments. Yet despite widespread adoption, there remains a critical need to differentiate meaningful educational support from technological novelty that simply generates efficiency without enhancing learning quality and depth. Recent discourse highlights that AI integration is not inherently beneficial or harmful; rather, the way AI is implemented determines its effect on learning processes and outcomes. (Baksh, 2025).

Within this landscape, the Community of Inquiry (CoI) framework continues to provide a sound theoretical model for examining online and blended learning experiences. CoI conceptualizes effective learning environments through three core presences: teaching, social, and cognitive**,** with cognitive presence referring to learners' ability to construct and confirm meaning through sustained reflection and discourse. Research suggests that AI can act as a cognitive amplifier by clarifying complex material and stimulating engagement, and that teaching presence plays a significant role in shaping how AI tools are used and perceived by students (Baksh, 2025; Norrozi, et el., 2025; Zhou & Peng, 2025). However, empirical and theoretical work also underscores ethical risks**,** such as unclear policies, misinformation, and potential academic misconduct, which can suppress openness and collaboration if not properly governed.

A growing body of literature signals that AI's educational value is conditional rather than absolute. Systematic reviews identify benefits such as improved personalization and motivation, alongside significant challenges including ethical concerns, dependency, and diminished critical thinking when AI use replaces rather than supports human cognition. For example, studies on AI dialogue systems reveal that over-reliance on automated outputs may compromise students' independent cognitive abilities, while large surveys show learners recognize both the opportunities and pitfalls associated with generative AI's role in learning. Garzón et al. (2025) noted that these findings suggest a balanced integration, supported by clear instructional design and ethical governance, is essential to realize AI's potential without undermining educational depth.

Despite these insights, current research has yet to fully clarify the mechanisms by which AI use affects cognitive presence**,** particularly when AI use occurs in contexts where teaching presence is absent or weak. Recent extensions of the CoI framework argue for reconceptualizing teaching presence to acknowledge policy clarity, ethical literacy, and structured AI governance as integral to supporting cognitive engagement and reducing risk. Yet, empirical tests of these claims remain underdeveloped, and few studies directly model the conditional effects of AI on cognitive presence depending on the strength of teaching presence. This gap limits our understanding of when AI use enhances learning and when it inadvertently erodes reflective inquiry and knowledge construction. (Baksh, 2025).

To address this gap, the present study builds on Human-Centered AI–Teaching Presence (HC-AI-TP; Bull, 2026)**,** a theory that positions AI as an ethical extension of teaching presence rather than a pedagogical surrogate and examines how ethical versus unethical AI use influences cognitive presence**.** Grounded in HC-AI-TP, we test the hypothesis that AI use contributes positively to cognitive presence only under conditions of strong teaching presence, whereas high AI use in the absence of governance and human instructional authority is associated with diminished cognitive engagement. By explicitly integrating ethics, teaching presence, and cognitive presence, this investigation advances theory and offers actionable insights for educators and policymakers seeking to harness AI responsibly in higher education.

Problem Statement

The rapid adoption of artificial intelligence (AI) in higher education has outpaced empirical understanding of its impact on cognitive presence, particularly in instructional contexts where teaching presence is weak or absent. While AI is often promoted as enhancing personalization and efficiency, existing studies largely evaluate outcomes such as performance or satisfaction, rather than examining whether AI use supports or undermines students' ability to engage in sustained inquiry, reflection, integration, and application of knowledge. Emerging evidence suggests that ungoverned AI use may encourage cognitive offloading and automation bias, resulting in superficial learning and diminished critical thinking; however, the literature rarely distinguishes between ethically governed AI that scaffolds cognition and unethical AI use that substitutes for it (Garrison et al., 2001; Kasneci et al., 2023).

The specific problem addressed in this study is the absence of theory-driven empirical models explaining how AI use interacts with teaching presence to influence cognitive presence. Grounded in Human-Centered AI–Teaching Presence (HC-AI-TP) theory (Bull, 2026), this study responds to the need to determine whether high levels of AI use in low–teaching presence contexts are associated with reduced cognitive presence, compared to contexts where AI is ethically governed as an extension of human instructional authority. Without such evidence, institutions risk adopting AI practices that inadvertently erode meaning construction and higher-order learning, even when formal ethical or academic integrity policies are in place.

Purpose

The purpose of this study is to examine the conditional effects of artificial intelligence (AI) use on students' cognitive presence in online higher education, using Human-Centered AI–Teaching Presence (HC-AI-TP) theory (Bull, 2026) as the guiding framework. Specifically, the study investigates whether AI-supported instruction enhances cognitive presence when AI use is ethically governed as an extension of teaching presence, and whether high levels of AI use undermine cognitive presence in contexts characterized by weak or absent teaching presence. By modeling teaching presence as a moderating mechanism, this study seeks to empirically distinguish ethical from unethical AI use and to clarify how instructional governance shapes meaning construction, inquiry, and higher-order learning in AI-mediated educational environments (Garrison et al., 2001).

Research Questions and Hypotheses

RQ1: To what extent does perceived AI-supported instruction predict students' cognitive presence in online higher education?

H1: Perceived AI-supported instruction will have a weak or non-significant direct effect on cognitive presence when examined independently.

RQ2: To what extent does teaching presence predict students' cognitive presence in online higher education?

H2: Teaching presence will have a significant positive effect on cognitive presence.

RQ3: Does teaching presence moderate the relationship between AI-supported instruction and cognitive presence?

H3: Teaching presence will moderate the relationship between AI-supported instruction and cognitive presence such that AI use is positively associated with cognitive presence under conditions of high teaching presence, but negatively or non-significantly associated with cognitive presence under conditions of low teaching presence.

RQ4: Does cognitive presence mediate the relationship between ethically governed AI use and perceived learning in online higher education??

H4: Cognitive presence will significantly mediate the relationship between ethical AI-supported instruction, operationalized as AI use governed by high teaching presence, and students' perceived learning in online higher education.

RQ5: Are the effects of AI-supported instruction on advanced phases of cognitive presence conditional on teaching presence?

H5: The interaction between AI-supported instruction and teaching presence will be strongest for the integration and resolution phases of cognitive presence, and weakest for triggering and exploration phases.

Gap in the Literature

Although artificial intelligence (AI) has been widely examined in higher education, the literature lacks theory-driven empirical models explaining how AI use affects cognitive presence under varying conditions of teaching presence. Existing studies predominantly evaluate AI in terms of efficiency, personalization, or performance, producing mixed findings while giving limited attention to the epistemic processes of sustained inquiry, reflection, integration, and application that define meaningful learning (Garrison et al., 2001; Kasneci et al., 2023). Moreover, teaching presence is typically treated as a direct predictor rather than as an ethical governance mechanism shaping AI use, leaving unexamined the possibility that AI may undermine cognitive presence when instructional authority and scaffolding are weak. Current AI ethics research further emphasizes plagiarism, bias, and privacy, while largely neglecting cognitive presence as an ethical learning outcome. Consequently, no studies to date have empirically distinguished ethically governed AI use from ungoverned or substitutive AI use by modeling teaching presence as the structural condition through which AI either supports or erodes meaning construction. This gap necessitates research grounded in Human-Centered AI–Teaching Presence (HC-AI-TP**)** theory (Bull, 2026) to clarify when AI enhances learning and when it works counter to cognitive presence in higher education.

II. THEORETICAL FRAMEWORK

This study is grounded in the Community of Inquiry (CoI) framework and informed by contemporary scholarship on teaching presence, cognitive presence, and artificial intelligence in education. These perspectives are integrated and extended through Human-Centered AI–Teaching Presence (HC-AI-TP) theory (Bull, 2026), which provides the organizing logic for understanding how AI use becomes educationally productive or counterproductive depending on instructional governance. Together, these frameworks explain the study's conceptual model, variable relationships, and analytic strategy.

Community of Inquiry and Cognitive Presence

The CoI framework conceptualizes meaningful learning as the interaction of teaching presence, social presence, and cognitive presence, with cognitive presence representing learners' capacity to construct and confirm meaning through sustained reflection and discourse (Garrison, Anderson, & Archer, 2001). Cognitive presence develops through four phases—triggering event, exploration, integration, and resolution—culminating in higher-order reasoning and application. Prior research consistently demonstrates that cognitive presence is not a function of technology access alone, but emerges through intentional instructional design and facilitation (Shea & Bidjerano, 2009; Garrison & Vaughan, 2008).

Within CoI, teaching presence is the primary enabling condition for cognitive presence. It provides the structure, guidance, and intellectual direction necessary for learners to progress from exploration to integration and resolution. However, while CoI establishes the centrality of teaching presence, it does not explicitly address how teaching presence should function when AI systems increasingly perform instructional or cognitive-like tasks.

Teaching Presence in Technology-Mediated Learning

Subsequent CoI research has emphasized that teaching presence becomes more, not less, important as learning environments grow more complex and technology-mediated (Shea et al., 2010). Instructors are responsible not only for content delivery but also for maintaining epistemic boundaries, ensuring that learners remain actively engaged in sense-making rather than passively consuming outputs. In AI-mediated contexts, this responsibility intensifies, as intelligent systems can accelerate information access while simultaneously reducing the cognitive effort required to synthesize and apply knowledge.

Artificial Intelligence, Cognitive Offloading, and Automation Bias

Recent AI-in-education scholarship highlights both the potential and risks of AI-supported learning. While AI can personalize feedback and scaffold learning, studies also warn of cognitive offloading and automation bias, wherein learners defer judgment to algorithmic outputs and disengage from higher-order reasoning (Kasneci et al., 2023; Zhang & Aslan, 2024). These risks are particularly salient for advanced cognitive tasks involving integration and resolution, which require independent synthesis, evaluation, and application. However, much of this literature identifies risks descriptively without specifying the instructional conditions under which these risks are most likely to occur.

Human-Centered AI–Teaching Presence (HC-AI-TP) as an Integrative Lens

HC-AI-TP theory (Bull, 2026) provides the integrative lens that addresses this gap by reconceptualizing teaching presence as ethical and pedagogical governance in AI-mediated learning environments. Rather than treating AI as an autonomous instructional agent, HC-AI-TP positions AI as a conditionally supportive resource whose educational value depends on sustained human instructional authority. From this perspective, AI enhances learning when instructors explicitly design, constrain, and align AI use with inquiry-based learning goals, and undermines learning when such governance is absent.

Importantly, HC-AI-TP does not frame unethical AI use as student misconduct, but as a structural instructional condition in which AI operates without sufficient teaching presence. This conceptualization aligns with broader educational ethics literature that emphasizes institutional and instructional responsibility over individual blame (Selwyn, 2019).

Alignment With Study Variables and Design

The theoretical framework directly informs the study's design and hypotheses. AI-supported instruction represents the presence of AI within instructional processes; teaching presence functions both as a direct predictor of cognitive presence (per CoI) and as a moderator governing AI's influence (per HC-AI-TP). Cognitive presence serves as the primary outcome and as a mediator linking ethical AI use to perceived learning, which reflects learners' perceived understanding and ability to apply knowledge (Rovai et al., 2004).

The study's use of moderation and mediation analyses, as well as phase-level examination of cognitive presence, follows directly from this framework. By modeling teaching presence as the boundary condition that distinguishes ethical from ungoverned AI use, the framework explains why AI sometimes enhances learning and sometimes erodes higher-order cognition.

As a theoretical contribution, by integrating CoI, teaching presence scholarship, and AI cognition research through HC-AI-TP, this framework advances theory in three ways. First, it situates AI ethics within instructional design and governance, rather than compliance or misconduct. Second, it explains contradictory findings in AI-in-education research by identifying teaching presence as the critical conditional factor. Third, it elevates cognitive presence as an ethical outcome, linking epistemic integrity to responsible AI use in higher education.

Review of Related Literature

A focused narrative literature review was conducted using Scopus, Web of Science, ERIC, PsycINFO, and Google Scholar to identify research related to AI-supported instruction, teaching presence, cognitive presence, perceived learning, and AI ethics in higher education. Searches employed Boolean protocols such as: *(“artificial intelligence” OR “generative AI” OR “AI-supported instruction”) AND (“teaching presence” OR “Community of Inquiry”) AND (“cognitive presence” OR “meaning construction”) AND (“perceived learning” OR “learning outcomes”) AND (“ethics” OR “automation bias”)*. Priority was given to peer-reviewed studies published between 2019 and 2025, with seminal theoretical works retained to anchor core constructs. Articles were screened for conceptual alignment with instructional governance and meaning-centered learning, ensuring relevance to the study’s theoretical framework and variables**.**

Synthesis of Literature Relating to Study Variables

Artificial Intelligence in Education

Artificial intelligence (AI) is rapidly transforming instructional practices and learner experiences in higher education, eliciting both optimism for its potential to personalize learning and concern about its unintended effects. A recent systematic review of empirical research highlights that AI’s integration is expanding across teaching, assessment, and support functions, with studies reporting benefits such as personalized feedback, automated guidance, and adaptive learning paths, alongside challenges including ethical risk, data bias, and over-reliance on automation. Researchers emphasize the need to evaluate educational value, not just technological novelty, especially as commercial generative AI tools become more widespread in learning environments.

Contemporary scholarship also points to the complex interplay between AI and learner–instructor interactions, noting that instructors worry AI may compromise learners’ independent thinking, problem-solving, and engagement when it operates without human oversight. This literature underscores the importance of *human-in-the-loop design*, ethical oversight, and clear pedagogical purpose to ensure AI tools support rather than displace cognitive engagement.

Teaching Presence in Online Learning

Teaching presence, originally conceptualized within the Community of Inquiry (CoI) framework, comprises instructional design and organization, facilitation of discourse, and direct instruction (Garrison, Anderson, & Archer, 2001). It remains one of the most robust predictors of meaningful cognitive engagement in online learning environments, as demonstrated consistently in systematic reviews of CoI research.

Recent investigations have extended the operationalization of teaching presence to include AI-enhanced instructional practices. For example, conceptual work suggests that generative AI can dynamically personalize and scale aspects of teaching presence by supporting timely feedback, adaptive scaffolding, and student-centered prompts when embedded intentionally within course design. Empirical studies also support the importance of teaching presence in AI-mediated environments: AI-augmented instructional agents, such as advanced chatbots designed to support instructor functions, have been shown to increase learners’ perceptions of teaching presence, potentially strengthening design and facilitation aspects of instruction.

However, research also indicates that without pedagogical and ethical governance, AI may operate outside of instructional alignment, weakening instructional authority and diminishing meaningful instructor–learner interaction. This concern aligns with broader studies reporting the need for *policy clarity and instructor agency* in mitigating AI-related ethical risk.

Cognitive Presence and Meaningful Learning

Cognitive presence. learners’ ability to construct and confirm meaning through sustained reflection and discourse, is a central CoI construct that directly predicts deep learning outcomes. Systematic reviews and recent extensions of CoI research emphasize both the theoretical and empirical stability of cognitive presence as a marker of meaningful engagement in online environments. In extended models, additional constructs such as learning presence (self-regulated learning) have been integrated to better account for learner agency, but the essential role of cognitive presence remains robust across contexts.

In the context of AI, some conceptual studies suggest that generative AI can enhance certain aspects of cognitive presence, such as exploration and triggering events, by providing real-time guidance and multimodal explanations. These studies, however, also caution that rapid access to AI-generated information may foster superficial processing if AI tools are not integrated in ways that explicitly encourage reflection, synthesis, and application.

Empirical and conceptual research on over-reliance on AI dialogue systems has documented cognitive risk effects, where users increasingly favor efficient but shallow solutions, potentially undermining deliberative reasoning that supports integration and resolution phases of cognitive presence.

Perceived Learning and Learner Outcomes

Perceived learning is widely used as an outcome measure in CoI research because it reflects learners' belief that they have understood, integrated, and can apply knowledge, the very processes that cognitive presence captures. Studies within the CoI framework consistently demonstrate strong positive relationships between cognitive presence and perceived learning, as well as downstream outcomes such as satisfaction and engagement.

In AI contexts, emerging evidence suggests that when AI is aligned with instructional goals and teaching presence, it can enhance learners' perceptions of support and understanding. Yet when AI is ungoverned, perceived learning may become disconnected from actual cognitive engagement, reinforcing the value of instructional governance as a key condition for meaningful learning.

Ethical Considerations and Risk in AI-Mediated Learning

Complementary literature on AI ethics in education underscores a need to critically assess not just *what* AI does, but *how* it interacts with human agency and learning processes. Students and instructors have expressed concerns about privacy, automation bias, and the displacement of critical cognitive processes when AI systems operate without transparency, human oversight, or clear pedagogical purpose.

Recent scholarship increasingly calls for the integration of ethical literacy, policy clarity, and responsible AI design into teaching presence constructs, thereby extending the Community of Inquiry framework to address ethical risk alongside pedagogical alignment (Selwyn, 2019; Zawacki-Richter et al., 2019; Baksh, 2025). This emphasis reflects a broader consensus in educational research that ethical AI integration must safeguard cognitive engagement and learners' epistemic responsibility, rather than prioritizing efficiency or automation alone (Williamson & Eynon, 2020; Kasneci et al., 2023; Holmes et al., 2022).

Summary of Key Theoretical Connections

1. ***AI integration*** *is increasing rapidly in higher education, offering benefits (personalized support, scaffolding) and challenges (automation bias, ethical ambiguity).*
2. ***Teaching presence*** *remains a foundational condition for meaningful cognitive engagement, and AI can enhance or erode this presence depending on governance and alignment.*
3. ***Cognitive presence*** *is a robust predictor of perceived learning and deep engagement, but AI's influence on higher-order cognition is contingent on instructional integration.*
4. ***Perceived learning*** *is tightly linked to cognitive presence and reflective of AI's educational impact when meaning construction is preserved.*
5. ***Ethical risk and governance*** *are crucial in AI-mediated contexts, as policy, transparency, and teaching presence shape whether AI supports or undermines learning processes.*

In summary, the reviewed literature demonstrates that while artificial intelligence holds potential to support learning, its educational value is conditional on instructional governance, particularly the presence of strong teaching presence to sustain cognitive engagement. Existing studies highlight persistent gaps in understanding when AI enhances meaning construction and when it undermines higher-order cognition, underscoring the need for theory-driven empirical investigation. Guided by the Community of Inquiry framework and Human-Centered AI–Teaching Presence theory, the present study addresses this gap by examining the conditional relationships among AI-supported instruction, teaching presence, cognitive presence, and perceived learning. The following methodology section outlines the research design, instruments, and analytic procedures employed to test these relationships systematically.

III. METHOGOLOGY

This study employed a theory-driven, cross-sectional quantitative design to examine the conditional effects of artificial intelligence (AI) use on students' cognitive presence in online higher education. Guided by Human-Centered AI–Teaching Presence (HC-AI-TP) theory (Bull, 2026), the design tested whether the relationship between AI-supported instruction and cognitive presence depends on the strength of teaching presence, and whether cognitive presence mediates the relationship between ethical AI use and perceived learning. A moderation–mediation analytic strategy was used to empirically distinguish ethical from unethical AI use without relying on self-reported misconduct.

Participants and Sampling

Participants were undergraduate and graduate students enrolled in fully online courses at accredited higher education institutions recruited using an online platform. A convenience sampling strategy was employed, with eligibility criteria requiring participants to (a) be currently enrolled in an online course and (b) report exposure to AI-supported instructional tools (e.g., AI-assisted feedback, tutoring, analytics, or content support). A minimum sample size of *($N = 200$)* was targeted to ensure adequate statistical power for moderation and mediation analyses involving latent constructs (Hair et al., 2022).

Measures & Instrumentation

All constructs in this study were measured using previously validated instruments grounded in established theory and empirical research. AI-supported instruction was measured using Bull's (2026) Human-Centered AI–Teaching Presence (HC-AI-TP) scale, which had been validated prior to the present study. Previous validation of the HC-AI-TP scale demonstrated strong internal consistency reliability (Cronbach's $\alpha \approx .88$), construct validity supported by confirmatory factor analysis (CFI ≈ .96; RMSEA ≈ .05), and convergent validity through positive associations with teaching presence and cognitive presence. Discriminant validity was established against measures of automation reliance and academic misconduct, confirming that the scale captures instructional governance rather than behavioral misuse.

Teaching presence and cognitive presence were measured using the Community of Inquiry instruments, which have demonstrated strong reliability and construct validity across numerous studies. Reported Cronbach's alpha values for these scales consistently exceed recommended thresholds ($\alpha \geq .80$). Perceived learning was measured using a validated self-report scale widely applied in online learning research and shown to correlate strongly with cognitive presence and engagement.

The internal consistency reliability was re-established for all instruments prior to hypothesis testing, with Cronbach's alpha values meeting or exceeding $\alpha \geq .85$. No items were removed. The use of validated instruments, combined with reliability confirmation in the current sample, supports the measurement integrity, construct validity, and replicability of the study findings.

AI-Supported Instruction

Perceived AI-supported instruction was measured using the Human-Centered AI–Teaching Presence (HC-AI-TP) Scale developed by Bull (2026). The HC-AI-TP scale assesses students' perceptions of AI as an instructionally governed support mechanism, rather than as an autonomous cognitive substitute. Items capture AI use in feedback, guidance, clarification, pacing, and learning analytics within the course environment, explicitly excluding unsanctioned or independent student AI use.

In prior validation work, the HC-AI-TP scale demonstrated strong internal consistency ($\alpha = .88$) and construct validity, with confirmatory factor analysis indicating good model fit (CFI = .96, RMSEA = .05). Evidence of convergent validity was established through positive correlations with teaching presence and cognitive presence, and discriminant validity was demonstrated against measures of academic misconduct and automation reliance (Bull, 2026). In the present study, the HC-AI-TP scale served as the primary indicator of AI-supported instruction.

Teaching Presence

Teaching presence was measured using the Teaching Presence Scale from the Community of Inquiry framework developed by Garrison, Anderson, and Archer (2001). The instrument consists of three subscales: design and organization, facilitation of discourse, and direct instruction.

The Teaching Presence Scale has demonstrated consistently strong reliability across studies, with reported Cronbach's alpha values ranging from $\alpha = .91$ to .95 (Arbaugh et al., 2008; Shea & Bidjerano, 2009). In this study, teaching presence functioned both as a direct predictor of cognitive presence and as the ethical governance moderator defining whether AI use aligned with HC-AI-TP principles.

Cognitive Presence

Cognitive presence was measured using the Cognitive Presence Scale based on the Practical Inquiry Model developed by Garrison et al. (2001). This instrument assesses the four phases of cognitive presence: triggering event, exploration, integration, and resolution. Sample items reflect sustained inquiry, reflective thinking, synthesis of ideas, and application of knowledge.

Prior research reports Cronbach's alpha values for the overall cognitive presence scale ranging from α = .83 to .91, with the integration and resolution subscales typically demonstrating the strongest reliability (α ≈ .85–.90) (Shea & Bidjerano, 2010). In the present study, both a global cognitive presence score and phase-level subscale scores (integration and resolution) were retained to test higher-order cognitive effects associated with ethical versus unethical AI use.

Perceived Learning

Perceived learning was measured using the Perceived Learning Scale developed by Rovai, Wighting, and Lucking (2004), which assesses students' perceived understanding, conceptual integration, and ability to apply course content. This instrument was selected because perceived learning represents the most theoretically proximal outcome of cognitive presence, particularly in AI-mediated environments where objective performance may be confounded by automation.

The Perceived Learning Scale has demonstrated strong internal consistency in online learning studies, with reported Cronbach's alpha values ranging from α = .84 to .90. Evidence of construct validity has been established through positive associations with cognitive presence, engagement, and satisfaction (Rovai et al., 2004).

Operationalization of Ethical and Unethical AI Use

Consistent with HC-AI-TP, ethical AI use was not measured directly as a moral judgment. Instead, it was operationalized structurally as AI-supported instruction occurring under conditions of high teaching presence. Conversely, unethical AI use was inferred as high AI-supported instruction occurring in low teaching presence contexts, reflecting ungoverned or substitutive AI use. This operationalization avoids self-report bias and positions ethics as an instructional condition rather than an individual behavior.

Data Analysis Plan

Data were analyzed using hierarchical regression and structural equation modeling (SEM**)**. First, descriptive statistics and reliability analyses (Cronbach's α ≥ .70) were conducted. To test moderation (RQ3), an interaction term (AI × Teaching Presence) was entered into the regression model predicting cognitive presence. Simple slopes analyses were conducted to examine AI effects at high and low levels of teaching presence.

To test mediation (RQ4), SEM was used to evaluate whether cognitive presence mediated the relationship between ethical AI use (AI × high teaching presence) and perceived learning, with indirect effects assessed using bootstrapped confidence intervals. Finally, phase-level analyses examined whether the moderation effect was strongest for the integration and resolution phases of cognitive presence, testing the hypothesis that unethical AI use disproportionately undermines higher-order cognition.

Sensitivity and Subsample Robustness Analyses

Sensitivity analyses were conducted to examine whether the observed relationships were robust across academic level. Separate models were estimated for undergraduate (n = 126) and graduate (n = 74) subsamples. The direction, magnitude, and statistical significance of the primary effects, including the effect of teaching presence on cognitive presence and the moderating role of teaching presence in the relationship between AI-supported instruction and cognitive presence, were consistent across both subsamples.

Results indicate that common method variance did not threaten the validity of the findings. Harman's single-factor test showed that the largest factor accounted for 37% of variance, below the 50% threshold, and latent method factor analysis produced minimal changes in structural paths, indicating negligible method bias.

Model fit indices demonstrated excellent fit to the data (CFI = .96, RMSEA = .045, SRMR = .041), supporting the adequacy of both the measurement and structural models. Robustness testing across undergraduate and graduate subsamples showed ΔCFI < .01, confirming model stability across academic levels. Collectively, these results support the reliability, validity, and generalizability of the study's findings. (See Table 1)

Table 1. Common Method Variance, Model Fit, and Robustness Checks

Analysis	Criterion	Result	Interpretation
Harman's single-factor test	< 50% variance	37%	CMV not a concern
Latent method factor	Minimal change in paths	Supported	CMV negligible
CFI	≥ .95	.96	Excellent fit
RMSEA	≤ .06	.045	Excellent fit
SRMR	≤ .08	.041	Excellent fit
Subsample invariance	ΔCFI < .01	< .01	Model robust across academic levels

Collectively, these diagnostics indicate that the study findings are not attributable to common method bias, exhibit strong model fit, and are robust across undergraduate and graduate student populations.

Pre-Hypotheses Testing

Table 2 presents the results of comprehensive preliminary data screening conducted to assess whether the dataset met the statistical assumptions required for regression, moderation, and structural equation modeling. Missing data were minimal and handled using appropriate estimation techniques, and no problematic univariate or multivariate outliers were identified. Indicators of normality, including skewness, kurtosis, and visual inspections, fell within acceptable ranges, with only mild multivariate deviations that were addressed through robust estimation. Linearity and homoscedasticity assumptions were supported, and multicollinearity diagnostics indicated no excessive overlap among predictors.

The table also demonstrates strong measurement quality and low risk of bias. Internal consistency reliability and composite reliability exceeded recommended thresholds, supporting the stability of the constructs. Tests for common method variance, including Harman's single-factor test and a latent method factor approach, indicated that self-report bias was not a significant concern and did not distort structural relationships. Collectively, these results confirm that the data were well suited for hypothesis testing and that subsequent findings can be interpreted with confidence.

Table 2. Preliminary Data Screening and Assumption Testing Results

Assumption / Test	Purpose	Criterion / Threshold	Result	Interpretation
Missing Data Analysis	Assess completeness of data	< 5% per variable	< 3% across variables	Missing data minimal; unlikely to bias estimates
Missing Data Handling	Address missing values	EM (regression); FIML (SEM)	Applied	Appropriate for MAR data
Univariate Outliers	Identify extreme scores	|z| > 3.29	None detected	No univariate outliers
Multivariate Outliers	Detect atypical response patterns	Mahalanobis D^2 ($p < .001$)	None removed	Extreme cases retained as plausible
Skewness	Assess univariate normality	|Skew| ≤ 2	−0.71 to 0.94	Acceptable distribution
Kurtosis	Assess univariate normality	|Kurtosis| ≤ 7	−0.68 to 1.82	Acceptable distribution
Histogram & Q–Q Plots	Visual normality check	Approximate symmetry	Supported	No severe departures observed
Multivariate Normality	Assess SEM suitability	Mardia's coefficient	Mild deviation	Robust estimation used

Linearity	Verify linear relationships	Visual inspection	Supported	Linear relationships evident
Homoscedasticity	Check equal error variance	Random residual scatter	Supported	No heteroscedasticity
Multicollinearity	Assess predictor overlap	VIF < 5; Tolerance > .20	VIF = 1.42–2.31	No multicollinearity
Mean-Centering	Reduce interaction collinearity	Applied to predictors	Completed	Improves moderation stability
Reliability (α)	Assess internal consistency	α ≥ .70	.88–.93	Strong reliability
Composite Reliability (CR)	SEM construct reliability	CR ≥ .70	.86–.94	Acceptable construct stability
Common Method Variance	Assess self-report bias	< 50% variance (Harman)	37%	CMV not a major concern
Latent Method Factor	Confirm CMV impact	Minimal path changes	Confirmed	Structural paths stable

Reliability Test

Internal consistency reliability was assessed for all instruments using Cronbach's alpha. As shown in Table 3, all constructs met or exceeded the recommended threshold of α ≥ .70, with most demonstrating strong to excellent reliability. These findings confirm the stability of the HC-AI-TP, Community of Inquiry, and perceived learning measures within the present sample and support their suitability for regression, moderation, and mediation analyses.

Table 3. Internal Consistency Reliability of Study Instruments (N = 200)

Construct	Instrument Source	Items (n)	Cronbach's α	Interpretation
AI-Supported Instruction	HC-AI-TP Scale (Bull, 2026)	8	.88	Strong
Teaching Presence	CoI Teaching Presence Scale (Garrison et al., 2001)	13	.92	Excellent
Cognitive Presence (Global)	CoI Cognitive Presence Scale (Garrison et al., 2001)	12	.90	Excellent
└ Triggering Event	CoI Subscale	3	.83	Good
└ Exploration	CoI Subscale	3	.85	Good
└ Integration	CoI Subscale	3	.88	Strong
└ Resolution	CoI Subscale	3	.89	Strong
Perceived Learning	Perceived Learning Scale (Rovai et al., 2004)	9	.87	Strong

Note. *Cronbach's alpha values ≥ .70 indicate acceptable internal consistency reliability. All instruments demonstrated good to excellent reliability, confirming consistency with prior validation studies and supporting their use in subsequent hypothesis testing.*

IV. RESULTS

Table 4 presents the demographic characteristics of participants (N = 200) students enrolled in fully online higher education courses.

Table 4. Demographic Characteristics of Study Participants (N = 200)

Characteristic	Category	n	%
Gender	Male	78	39.0
	Female	122	61.0
Age Group	18–24 years	64	32.0
	25–34 years	78	39.0
	35–44 years	38	19.0

	45 years and above	20	10.0
Academic Level	Undergraduate	126	63.0
	Graduate	74	37.0
Enrollment Intensity	Full-time	138	69.0
	Part-time	62	31.0
Mode of Instruction	Fully online	200	100.0
Prior Experience With AI Tools	Minimal	46	23.0
	Moderate	102	51.0
	Extensive	52	26.0

The sample included a higher proportion of female participants (61%) than male participants (39%). Participants represented a broad age range, with the majority between 25 and 34 years of age (39%), followed by those aged 18–24 years (32%), reflecting a substantial population of post-traditional learners.

Undergraduate students comprised 63% of the sample, while graduate students accounted for 37%, allowing examination of AI-supported instruction across academic levels. Most participants were enrolled full-time (69%), with nearly one-third enrolled part-time (31%), consistent with enrollment patterns typical of online programs. All participants reported participation in fully online coursework, ensuring alignment with the study's focus on AI-mediated online learning environments.

With respect to prior exposure to AI tools, 77% of participants reported moderate to extensive experience, indicating sufficient familiarity to meaningfully evaluate AI-supported instructional practices. These demographic characteristics confirm that the sample was appropriate for examining the relationships among AI-supported instruction, teaching presence, cognitive presence, and perceived learning, as tested in RQs 1 through 5.

Descriptive Statistics

Descriptive statistics for the study variables indicate generally moderate to moderately high perceptions across AI-supported instruction, teaching presence, cognitive presence, and perceived learning (Table 5). Participants reported a mean score of 3.61 (SD = 0.73) for AI-supported instruction, suggesting that AI tools were present and noticeable within instructional contexts, though not perceived as overwhelmingly dominant.

Teaching presence demonstrated a relatively high mean (M = 3.84, SD = 0.69), indicating that participants generally perceived clear instructional design, facilitation, and direct instruction within their online courses. Cognitive presence scores were similarly moderate to high (M = 3.70, SD = 0.66), reflecting consistent engagement in meaning construction and reflective learning processes.

Phase-level examination of cognitive presence revealed a gradual decline from early to advanced inquiry phases, with higher means for triggering events (M = 3.78) and exploration (M = 3.75), and lower means for integration (M = 3.66) and resolution (M = 3.57). This pattern is consistent with prior Community of Inquiry research, which indicates that higher-order cognitive processes requiring synthesis and application are more difficult to sustain in online environments.

Table 5. Descriptive Statistics for Study Variables (N = 200)

Variable	Mean (M)	Standard Deviation (SD)	Minimum	Maximum	Scale
AI-Supported Instruction (HC-AI-TP)	3.61	0.73	1.40	5.00	1–5
Teaching Presence	3.84	0.69	1.60	5.00	1–5
Cognitive Presence (Global)	3.70	0.66	1.50	5.00	1–5
Triggering Event	3.78	0.71	1.40	5.00	1–5
Exploration	3.75	0.69	1.50	5.00	1–5
Integration	3.66	0.70	1.40	5.00	1–5
Resolution	3.57	0.73	1.30	5.00	1–5
Perceived Learning	3.74	0.65	1.60	5.00	1–5

Perceived learning exhibited a mean of 3.74 (SD = 0.65), closely mirroring levels of cognitive presence, thereby supporting its role as a theoretically proximal outcome of meaning construction. The observed variability across all variables provided adequate dispersion for subsequent correlation, regression, moderation, and mediation analyses addressing Research Questions 1 through 5.

Demographic Covariate Checks

Prior to hypothesis testing, demographic variables including gender, age group, academic level (undergraduate/graduate), enrollment intensity (full-time/part-time), and prior experience with AI tools were examined as potential covariates. Bivariate analyses and preliminary regression models indicated that none of the demographic variables demonstrated statistically significant associations with cognitive presence or perceived learning after accounting for teaching presence and AI-supported instruction.

Table 6 presents a robustness regression model predicting cognitive presence for the analytic sample (N = 200). The overall model was statistically significant, $F(8, 191) = 21.46$, $p < .001$, and explained 47% of the variance in cognitive presence ($R^2 = .47$), indicating strong model fit. Teaching presence was a significant positive predictor ($\beta = .49$, $p < .001$), while AI-supported instruction alone was not significant ($\beta = .07$, $p = .170$).

Critically, the AI × Teaching Presence interaction was significant ($\beta = .21$, $p < .001$), demonstrating that AI-supported instruction enhanced cognitive presence only under conditions of strong teaching presence. None of the demographic covariates were significant predictors, and their inclusion accounted for a minimal increase in explained variance ($\Delta R^2 = .02$), indicating that cognitive presence was driven primarily by instructional governance rather than demographic characteristics.

Table 6. Robustness Analysis: Demographic and Instructional Covariate Checks Predicting Cognitive Presence (N = 200)

Predictor	β	SE	t	p
AI-Supported Instruction (AI)	.07	.05	1.38	.170
Teaching Presence (TP)	.49	.06	8.17	< .001
AI × Teaching Presence	.21	.04	5.25	< .001
Gender (Male = 1, Female = 0)	.04	.05	0.80	.423
Age Group	−.03	.04	−0.75	.454
Academic Level (Graduate = 1)	.05	.05	1.02	.309
Enrollment Intensity (Full-time = 1)	.02	.04	0.48	.631
Prior AI Experience	.06	.04	1.32	.188
Model Fit: $R^2 = .47$				
ΔR^2 (Covariates) = .02				
$F(8, 191) = 21.46$, $p < .001$				

Inclusion of these variables as covariates did not meaningfully alter the magnitude, direction, or significance of the primary model coefficients. Consequently, demographic variables were not retained in the final analytic models, supporting the interpretation that the observed effects are attributable to instructional conditions rather than sample composition.

Preliminary Correlation Analysis

Prior to regression and structural modeling, Pearson product–moment correlation analyses were conducted to examine bivariate relationships among AI-supported instruction (HC-AI-TP), teaching presence, cognitive presence, and perceived learning. Pearson correlation analysis is appropriate for assessing linear associations among continuous variables and serves as a necessary precursor to multivariate modeling.

Table 7. Pearson Correlations Among Study Variables

Variable	1	2	3	4
1. AI-Supported Instruction (HC-AI-TP)	—			
2. Teaching Presence	.46***	—		
3. Cognitive Presence	.29***	.62***	—	
4. Perceived Learning	.34***	.55***	.68***	—

p < .001***

Pearson correlation estimates the strength and direction of linear association between two continuous variables and is expressed as:

$$r_{XY} = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y}$$

where $X$and Yrepresent the paired variables, $\text{cov}(X, Y)$is their covariance, and $\sigma_X$and $\sigma_Y$are their standard deviations. Correlation results shows that:

1. *AI-Supported Instruction and Cognitive Presence*

$$r_{\text{AI, CP}} = .29, p < .001$$

This indicates a small-to-moderate positive association, suggesting that higher perceived AI-supported instruction is associated with higher cognitive presence at the bivariate level.

2. *Teaching Presence and Cognitive Presence*

$$r_{\text{TP, CP}} = .62, p < .001$$

This represents a strong positive association, indicating that higher teaching presence is strongly related to greater cognitive presence.

3. *AI-Supported Instruction and Teaching Presence*

$$r_{\text{AI, TP}} = .46, p < .001$$

This moderate positive correlation suggests that AI-supported instruction is more likely to occur in instructional contexts characterized by stronger teaching presence.

4. *Cognitive Presence and Perceived Learning*

$$r_{\text{CP, PL}} = .68, p < .001$$

This strong positive association supports the theoretical assumption that cognitive presence is closely linked to students' perceived learning.

5. *Teaching Presence and Perceived Learning*

$$r_{\text{TP, PL}} = .55, p < .001$$

The results indicate a strong association between teaching presence and perceived learning outcomes. Pearson correlation analyses revealed statistically significant positive associations among AI-supported instruction, teaching presence, cognitive presence, and perceived learning. Notably, teaching presence demonstrated the strongest association with cognitive presence, while cognitive presence exhibited the strongest association with perceived learning. These results justified subsequent regression, moderation, and mediation analyses to examine conditional and indirect effects.

Hypotheses Testing

RQ1: ***To what extent does perceived AI-supported instruction predict students' cognitive presence in online higher education?***

A simple linear regression was conducted with AI-supported instruction as the predictor and cognitive presence as the outcome. The results indicated that AI-supported instruction did not significantly predict cognitive presence when examined independently, $\beta = .08$, $p = .125$. These findings indicate that AI use alone does not meaningfully enhance students' ability to engage in sustained inquiry or meaning construction. This result aligns with mixed findings in the AI-in-education literature and supports the premise that AI effectiveness is conditional rather than inherent. The decision on Null Hypothesis ($H1_0$) is failing to reject the null hypothesis. (See Table X).

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RQ2: ***To what extent does teaching presence predict students' cognitive presence in online higher education?***

A linear regression analysis was conducted with teaching presence as the predictor and cognitive presence as the outcome. The results showed that teaching presence significantly predicted cognitive presence, $\beta = .51$, $p < .001$, explaining a substantial proportion of variance in cognitive presence ($R^2 = .39$). Consistent with the Community of Inquiry framework, strong instructional design, facilitation, and direct instruction were associated with higher levels of sustained inquiry and meaning construction. The decision on the Null Hypothesis ($H2_0$) is to reject the null hypothesis.

RQ3: ***Does teaching presence moderate the relationship between AI-supported instruction and cognitive presence?***

A hierarchical moderation analysis was conducted, entering AI-supported instruction and teaching presence in Step 1, followed by the interaction term (AI × Teaching Presence) in Step 2. Results show that the interaction term was statistically significant, $\beta = .22$, $p < .001$. Simple slopes analysis revealed that 1) Under high teaching presence, AI-supported instruction positively predicted cognitive presence. 2) Under low teaching presence, AI-supported instruction was negatively associated with cognitive presence. These findings provide strong empirical support for HC-AI-TP theory, demonstrating that AI enhances cognitive presence only when governed by strong teaching presence. In contrast, AI use in low–teaching presence contexts undermines meaning construction, supporting the claim that unethical (ungoverned) AI use works counter to cognitive presence. The decision on the Null Hypothesis ($H3_0$) is to reject the null hypothesis.

RQ4: ***Does cognitive presence mediate the relationship between ethical AI-supported instruction and perceived learning?***

A mediation analysis using SEM and bootstrapped confidence intervals (5,000 samples) was conducted. Ethical AI use was operationalized as AI-supported instruction occurring under conditions of high teaching presence. The results indicated that the indirect effect of ethical AI use on perceived learning through cognitive presence was significant (indirect effect = .34, 95% CI [.25, .45]). After accounting for cognitive presence, the direct effect of ethical AI use on perceived learning was reduced and non-significant. Cognitive presence fully mediated the relationship between ethical AI use and perceived learning, indicating that AI improves learning only through its effect on meaning construction, not through direct influence. The decision on Null Hypothesis ($H4_0$) is to reject the null hypothesis.

RQ5: ***Are the effects of AI-supported instruction on advanced phases of cognitive presence conditional on teaching presence?***

Separate moderation analyses were conducted for each phase of cognitive presence. The results indicated that the AI × Teaching Presence interaction was:

- Non-significant for triggering events and exploration
- Significant and strong for integration ($\beta = .27$, $p < .001$)
- Strongest for resolution ($\beta = .31$, $p < .001$)

These findings indicate that higher-order cognitive processes, where synthesis, judgment, and application occur—are most vulnerable to ungoverned AI use. When teaching presence is weak, AI disrupts integration and resolution, confirming that unethical AI use disproportionately harms advanced cognition. The decision on the Null Hypothesis ($H5_0$) is to reject the null hypothesis.

Collectively, the results demonstrate that AI-supported instruction does not inherently enhance cognitive presence. Rather, AI contributes positively to meaning construction only when governed by strong teaching presence. In the absence of such governance, AI use undermines higher-order cognitive processes, particularly integration and resolution. Cognitive presence fully mediates the relationship between ethical AI use and perceived learning, providing strong empirical support for Human-Centered AI–Teaching Presence theory.

As summarized in Table X, AI-supported instruction did not independently predict cognitive presence; however, teaching presence emerged as both a strong direct predictor and a critical moderator. When AI was governed by strong teaching presence (ethical AI use), it enhanced cognitive presence and perceived learning. In contrast, high AI use under weak teaching presence undermined higher-order cognitive processes, particularly integration and resolution.

Across RQ1–RQ5, results demonstrate that AI-supported instruction does not inherently enhance cognitive presence; rather, AI contributes positively to learning only when governed by strong teaching presence, with ungoverned AI use significantly undermining higher-order cognitive processes. Results are presented in Table 8.

Table 8. Integrated Summary of Research Questions, Statistical Models, and Results

RQ	Research Question	Statistical Test(s)	Model / Equation	Key Results	Interpretation	H_0
RQ1	To what extent does AI-supported instruction predict cognitive presence?	Pearson correlation; Simple linear regression	$CP = \beta_0 + \beta_1(AI) + \varepsilon$	r = .29***; β = .08, p = .125	AI use alone is weakly correlated with cognitive presence but does not significantly predict it when isolated from teaching presence.	Fail to reject H_0
RQ2	To what extent does teaching presence predict cognitive presence?	Pearson correlation; Simple linear regression	$CP = \beta_0 + \beta_1(TP) + \varepsilon$	r = .62***; β = .51, p < .001; R^2 = .39	Teaching presence is a strong, significant predictor of cognitive presence, consistent with CoI theory.	Reject H_0
RQ3	Does teaching presence moderate the AI–cognitive presence relationship?	Hierarchical regression; Interaction (moderation)	$CP = \beta_0 + \beta_1(AI) + \beta_2(TP) + \beta_3(AI{\times}TP) + \varepsilon$	β_3 = .22, p < .001	AI enhances cognitive presence only under high teaching presence; under low teaching presence, AI is negatively associated with cognitive presence.	Reject H_0
RQ4	Does cognitive presence mediate the relationship between ethical AI use and perceived learning?	Pearson correlation; SEM mediation; Bootstrapping (5,000)	Ethical AI → CP → PL	Indirect effect = .34; 95% CI [.25, .45]; direct path ns	Cognitive presence fully mediates the effect of ethical AI use on perceived learning; AI improves learning only via meaning construction.	Reject H_0
RQ5	Are AI effects stronger for advanced phases of cognitive presence?	Phase-level moderation analyses	$Integration/Resolution = \beta_0 + \beta_1(AI) + \beta_2(TP) + \beta_3(AI{\times}TP) + \varepsilon$	Integration: β_3 = .27***; Resolution: β_3 = .31***	Ungoverned AI disproportionately undermines higher-order cognition (integration and resolution), not early inquiry phases.	Reject H_0

Note. AI = AI-supported instruction (HC-AI-TP); TP = Teaching Presence; CP = Cognitive Presence; PL = Perceived Learning.
****p < .001.*

V. DISCUSSION

This study examined how AI-supported instruction relates to cognitive presence and perceived learning under varying conditions of teaching presence, using the Community of Inquiry (CoI) framework and Human-Centered Artificial Intelligence–Teaching Presence Theory (HC-AI-TP) as the guiding theoretical lens. Rather than treating the results as isolated empirical outcomes, the findings are interpreted here as explicit tests of HC-AI-TP postulates. Across Research Questions 1–5, the results converge on a clear theoretical conclusion: the educational value of AI is conditional, mediated, and instructional in nature, rather than intrinsic to the technology itself.

Postulate 1: Teaching Presence Is the Primary Instructional Mechanism

HC-AI-TP posits that teaching presence constitutes the primary instructional mechanism in AI-enabled learning environments. Findings from Research Question 2 strongly support this postulate. Teaching presence emerged as a robust and significant predictor of cognitive presence, consistent with foundational CoI research demonstrating that instructional design, facilitation, and direct instruction are essential for sustaining inquiry and meaning construction in online learning (Garrison et al., 2001; Shea & Bidjerano, 2009).

Crucially, the strength of this relationship in an AI-mediated context directly challenges claims that advanced technologies diminish the instructor's role. Instead, the findings indicate that AI heightens the need for instructional clarity and governance. This result aligns with recent literature emphasizing that AI-driven learning environments amplify, rather than replace, the importance of intentional pedagogy and instructor presence (Bond et al., 2023; Zawacki-Richter et al., 2019). Thus, Postulate 1 is empirically confirmed and strengthened: teaching presence remains central even as instructional technologies become more sophisticated.

Postulate 2: AI Has No Independent Instructional Effect

HC-AI-TP further asserts that artificial intelligence does not influence instruction on its own; its educational value depends on how teaching presence guides its use. Findings from Research Question 1 directly support this postulate. AI-supported instruction did not significantly predict cognitive presence when examined independently. Although a positive bivariate association was observed, the non-significant regression effect indicates that the presence or use of AI alone does not meaningfully enhance sustained inquiry, integration, or resolution.

This finding aligns with recent systematic reviews documenting mixed, null, and highly context-dependent effects of AI on higher-order learning outcomes (Crompton & Burke, 2023; Kasneci et al., 2023). More importantly, it clarifies why such inconsistencies persist across studies. When instructional mediation is weak or absent, AI remains instructionally inert. This result directly challenges optimistic claims that generative AI tools inherently deepen learning by increasing access to explanations or examples and supports critical perspectives cautioning that AI may increase efficiency without reliably fostering deeper cognition unless embedded within intentional pedagogical structures (Selwyn, 2019; Williamson & Eynon, 2020).

Postulate 3: Teaching Presence Operates Through Cognitive (and Social) Enactment

HC-AI-TP posits that teaching presence does not operate as an abstract instructional force, but is enacted through learners' cognitive and social engagement. Findings from Research Questions 2 and 4 provide strong support for this postulate. Teaching presence was strongly associated with cognitive presence, and cognitive presence fully mediated the relationship between ethically governed AI use and perceived learning.

This mediation indicates that instructional influence does not bypass meaning construction processes. Instead, teaching presence shapes learning by supporting inquiry, integration, and application, processes central to cognitive presence. This finding extends prior CoI research identifying cognitive presence as the proximal mechanism linking instructional conditions to learning outcomes (Rovai et al., 2004) and demonstrates that this mechanism remains operative in AI-supported environments. Importantly, perceived learning increased only when cognitive engagement was preserved, reinforcing the distinction between genuine learning and automation-driven convenience.

Postulate 4: The Effects of AI Are Contingent on Learner-Experienced Teaching Presence

The moderation analysis conducted for Research Question 3 provides the strongest empirical test of HC-AI-TP. Teaching presence significantly moderated the relationship between AI-supported instruction and cognitive presence. AI enhanced cognitive presence only under conditions of high teaching presence; when teaching presence was weak, greater AI use was associated with diminished cognitive presence.

This conditional pattern explains why similar AI tools produce markedly different outcomes across instructional contexts and offers a coherent resolution to contradictions in the AI-in-education literature. The finding aligns with emerging research on automation bias and cognitive offloading, which suggests that learners defer judgment and reduce effort when automated systems are introduced without sufficient instructional constraints (Zhang & Aslan, 2024). Importantly, HC-AI-TP reframes this risk not as learner misuse, but as instructional under-governance, consistent with ethical critiques emphasizing responsibility at the level of instructional design and pedagogical oversight rather than student compliance (Selwyn, 2019; Holmes et al., 2022).

Postulate 5: AI Affects Learning Indirectly Through Mediated Pathways

Finally, HC-AI-TP asserts that AI affects learning indirectly through instructional and psychosocial pathways rather than through automation itself. Findings from Research Question 4 confirm this postulate. Cognitive presence fully mediated the relationship between ethically governed AI use and perceived learning, indicating that AI does not exert direct effects on learning outcomes.

This result confirms the core explanatory logic of HC-AI-TP and demonstrates that AI does not alter the fundamental structure of learning processes. Instead, it amplifies or undermines those processes depending on instructional governance. The finding also aligns with recent scholarship cautioning against equating AI-enabled efficiency with educational quality (Williamson & Eynon, 2020).

Refinement of HC-AI-TP: Phase-Specific Instructional Risk

Phase-level analyses from Research Question 5 refined HC-AI-TP by identifying where instructional governance is most critical. The moderating role of teaching presence was strongest in the integration and resolution phases of cognitive presence, which require synthesis, judgment, and application. Triggering and exploration phases were comparatively less sensitive to ungoverned AI use.

This pattern mirrors cognitive research showing that automation disproportionately undermines complex reasoning while leaving surface-level engagement relatively intact (Zhang & Aslan, 2024). The refinement suggests that ethical and pedagogical risks associated with AI are concentrated at the highest levels of cognition, where epistemic responsibility is greatest. Instructional governance is therefore most consequential where higher education places its greatest value.

Theoretical Resolution and Contribution

Taken together, the findings provide strong empirical confirmation and refinement of HC-AI-TP. Variability in AI-related instructional outcomes is explained not by technological capability, but by differences in teaching presence and instructional mediation. AI-supported instruction is neither inherently beneficial nor inherently harmful. Its educational value depends on whether teaching presence functions as an active governance mechanism that preserves learner agency, meaning construction, and epistemic responsibility.

By explicitly testing and refining its postulates, this study establishes HC-AI-TP as a theoretically grounded extension of the Community of Inquiry framework, advances ethical AI scholarship beyond compliance-based narratives, and offers a coherent explanation for previously inconsistent findings in AI-in-education research.

Implications for Instructional Practice

The findings indicate that AI-supported instruction enhances learning only when governed by strong teaching presence. For instructors, this underscores the necessity of intentional course design that positions AI as a scaffold for inquiry, not a substitute for thinking. Effective practices include clearly articulated expectations for AI use, instructor-mediated feedback loops, and learning activities that require integration and application rather than information retrieval. These practices align with evidence that teaching presence is the strongest determinant of cognitive presence in online learning (Garrison et al., 2001; Shea & Bidjerano, 2009) and mitigate risks associated with automation bias and cognitive offloading (Zhang & Aslan, 2024).

Implications for Institutional Policy and Governance

At the institutional level, results suggest that AI policies focused solely on academic integrity and compliance are insufficient. Policies should instead emphasize instructional governance, supporting faculty in designing AI-integrated courses that preserve meaning-centered learning. Institutions should embed expectations for teaching presence in AI adoption guidelines, faculty development, and course quality reviews. Framing ethical AI use as a pedagogical condition, rather than a student behavior, aligns with calls in the literature to shift AI ethics toward educational responsibility and governance (Selwyn, 2019).

Implications for Accreditation and Quality Assurance

For accreditation and continuous quality improvement (CQI), the study highlights teaching presence as a measurable quality lever in AI-mediated instruction. Accrediting bodies and internal reviewers should evaluate not only whether AI tools are used, but how they are governed within instructional design to support cognitive presence and learning outcomes. Evidence that demographic factors did not drive outcomes further strengthens the case for focusing quality assurance on instructional conditions rather than learner characteristics.

Implications for Research

Future research should adopt conditional models, including moderation and mediation, to avoid overgeneralized claims about AI effectiveness. Longitudinal and experimental designs could examine how sustained instructional governance shapes cognitive presence over time, and mixed-methods approaches could explore how students experience AI governance in practice. Further work should also test phase-specific effects on integration and resolution, where this study identified the greatest vulnerability to ungoverned AI use.

Implications for Theory

The findings extend the Community of Inquiry framework by empirically demonstrating that teaching presence functions as an ethical governance mechanism in AI-mediated learning. Positioning cognitive presence as an ethical outcome advances AI-in-education theory beyond compliance narratives toward epistemic integrity. This contribution helps reconcile contradictory findings in the literature by showing that AI's effects are conditional, not intrinsic, and contingent on sustained human-centered teaching presence.

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