ISSN 2348-1196 (print)
International Journal of Computer Science and Information Technology Research ISSN 2348-120X (online)
Vol. 14, Issue 1, pp: (19-44), Month: January - March 2026, Available at: www.researchpublish.com

Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP): *A theory of instructional amplification in AI-enabled education*

Dr. David Augustine Bull

DBA, Ph.D., MBA., M.Sc., BSc., PMP., CMHC.

American InterContinental University System, School of Business

DOI: https://doi.org/10.5281/zenodo.18359914

Published Date: 24-January-2026

Abstract: **The rapid integration of artificial intelligence (AI) into higher education has outpaced the development of coherent theoretical frameworks explaining how AI influences instructional processes. Existing research often adopts technologically deterministic assumptions, attributing instructional effects directly to AI systems while under-theorizing the role of human pedagogy. This study introduces and confirms Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP), a middle-range explanatory theory that conceptualizes AI as instructionally neutral until enacted through human teaching presence. Using a theory-confirmation design with a sample of 200 participants, six theory-derived hypotheses were tested to evaluate the internal coherence, directional logic, and boundary conditions of the theory. Ordinary least squares regression analyses demonstrated that Human-Centered AI strongly predicted Teaching Presence ($\beta = .60$, $R^2 = .36$, $p < .001$). Teaching Presence, in turn, significantly predicted both Social Presence ($\beta = .55$, $R^2 = .30$, $p < .001$) and Cognitive Presence ($\beta = .58$, $R^2 = .34$, $p < .001$). Mediation analyses using bootstrapped indirect effects confirmed that Teaching Presence fully mediated the relationships between Human-Centered AI and both Social Presence (indirect $\beta = .33$, 95% CI [.24, .43]) and Cognitive Presence (indirect $\beta = .35$, 95% CI [.26, .45]). Direct effects from Human-Centered AI to Social and Cognitive Presence were non-significant, confirming the theory's boundary condition and rejecting technologically deterministic explanations. Collectively, the findings confirm the internal coherence and empirical plausibility of HC-AI-TP, establishing Teaching Presence as the central mechanism through which AI influences instructional environments and providing a theoretically grounded foundation for subsequent application and outcome-focused research.**

Keywords: **human-centered artificial intelligence, teaching presence, theory confirmation, instructional mediation, higher education.**

"Artificial intelligence does not teach; it reveals the conditions under which teaching remains human."
— Bull, 2026

1. INTRODUCTION

Artificial intelligence does not introduce a fundamentally new problem to education; rather, it exposes a longstanding theoretical ambiguity concerning the nature of teaching itself. As AI systems increasingly participate in instructional activities, such as feedback generation, content sequencing, and learner monitoring, they make visible the assumptions educators and institutions hold about whether teaching is a technical function or a human process. Proceeding from the premise that "artificial intelligence does not teach; it reveals the conditions under which teaching remains human" (Bull, 2026), this work argues that the educational impact of AI cannot be understood apart from teaching presence as a human, relational, and intentional instructional mechanism.

ISSN 2348-1196 (print)
International Journal of Computer Science and Information Technology Research ISSN 2348-120X (online)
Vol. 14, Issue 1, pp: (19-44), Month: January - March 2026, Available at: www.researchpublish.com

Artificial intelligence has become increasingly embedded in higher education, reshaping instructional design, assessment practices, feedback mechanisms, and student support systems. Adaptive learning platforms, automated feedback tools, predictive analytics, and generative AI applications are now routinely integrated into online and blended learning environments. As a result, AI is no longer peripheral to instruction but has become a consequential presence within the teaching–learning process itself (Holmes et al., 2019; Zawacki-Richter et al., 2019). Correspondingly, scholarly interest in AI-enabled education has expanded rapidly, producing a growing body of research examining AI's influence on learning performance, engagement, efficiency, satisfaction, and persistence (Bond et al., 2023).

The significance of this premise lies in its explanatory implications. If artificial intelligence does not function as a pedagogical agent, then existing frameworks that treat AI as a direct cause of learning outcomes are conceptually incomplete. Mixed empirical findings in AI-enabled education may therefore reflect not technological inconsistency, but theoretical misattribution. Current instructional and technology models describe AI adoption or predict usage patterns, yet they do not explain how AI interacts with teaching presence as a human instructional mechanism (Whetten, 1989; Gregor, 2006). This unresolved explanatory gap necessitates the development of a theory capable of specifying the conditions under which AI amplifies, rather than erodes, human teaching.

Despite this proliferation of research, the literature remains theoretically unsettled. Empirical findings concerning the educational effects of AI are frequently inconsistent, context-dependent, and difficult to reconcile. Large-scale syntheses of the field similarly conclude that reported benefits of AI in education vary widely by pedagogical context, instructional design, and degree of human mediation, underscoring the absence of a unifying explanatory framework (Garzón et al., 2025). While some studies report improvements in efficiency or short-term academic outcomes, others document neutral effects or unintended consequences, including diminished instructor visibility, weakened relational connection, and reduced student engagement (Selwyn, 2019; Azevedo et al., 2022). Such mixed findings suggest not merely empirical variability but a deeper conceptual problem: the absence of a coherent theory explaining how artificial intelligence interacts with human instructional processes.

Much of the existing literature implicitly assumes that technological capability translates into pedagogical effectiveness. Artificial intelligence is often treated as a neutral instructional tool, a delivery mechanism, or, in some cases, as a quasi-instructional agent capable of performing teaching functions independently (Williamson & Eynon, 2020). Prevailing assumptions in AI-in-education research frequently obscure the role of human agency, instructional intentionality, and relational presence in shaping learning experiences. As a result, artificial intelligence is often positioned as an independent causal factor rather than as a condition embedded within human-governed instructional and institutional systems. This perspective ignores the ways in which teachers and students make deliberate decisions about how AI tools are used, limited, and integrated into teaching and learning (Selwyn, 2022; Williamson & Eynon, 2020).

This theoretical ambiguity has practical consequences. Institutions increasingly adopt AI technologies without a principled framework for evaluating their impact on teaching quality or student experience (Selwyn et al., 2020). Faculty are encouraged to integrate AI tools while lacking theoretical guidance that preserves instructional authority and pedagogical coherence (Castañeda & Selwyn, 2018). These developments underscore the need for a theory capable of explaining not whether AI can be used in education, but how and under what conditions AI contributes to meaningful teaching and learning.

In response to this gap, the present article advances Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP). The theory conceptualizes artificial intelligence not as a pedagogical actor, but as a human-dependent instructional amplifier whose educational influence emerges only through teaching presence enacted within social and cognitive learning systems.

PHASE 1: THEORY FORMATION (CONCEPTUAL LEGITIMATION)

Step 1. Defining the Phenomenon and the Problem Space

The phenomenon motivating the development of Human-Centered Artificial Intelligence and Teaching Presence Theory is the expanding use of artificial intelligence in instructional contexts traditionally governed by human judgment and relational pedagogy. AI systems increasingly participate in activities such as feedback provision, instructional sequencing, assessment support, and learner monitoring, functions historically associated with teaching presence (Holmes et al., 2022). This shift has altered not only instructional workflows but also the perceived boundaries between technology and pedagogy.

Yet, the literature lacks conceptual consensus regarding the instructional status of AI. Across studies, AI is variably framed as a neutral support tool, an efficiency-enhancing mechanism, a personalization engine, or a substitute for instructional interaction (Zawacki-Richter et al., 2019). These competing conceptualizations reflect a fragmented understanding of AI's pedagogical role and generate incompatible assumptions about causality. In many cases, AI is treated as if its presence alone is sufficient to influence learning outcomes, without adequate attention to the instructional processes through which such influence would occur.

This conceptual fragmentation is mirrored by theoretical fragmentation. Established instructional frameworks, including the Community of Inquiry framework developed by Garrison, Anderson, and Archer (2000), are frequently cited in AI-related studies but rarely extended to theorize AI as an instructional influence. Similarly, technology acceptance and adoption models explain why individuals use technology but provide limited insight into how technology reshapes instructional relationships once adoption has occurred (Venkatesh et al., 2016). Learning analytics and AI-centered frameworks emphasize optimization, prediction, and efficiency, yet often under-theorize relational and pedagogical dynamics central to teaching and learning (Williamson, 2020).

As a result, much of the AI-in-education literature remains descriptive rather than explanatory. Studies report associations between AI use and educational outcomes without specifying the instructional pathways through which those outcomes arise. As Whetten (1989) argues, a theoretical contribution must clearly articulate what constructs matter, how they are related, and why those relationships exist. In the current literature, these elements are often addressed in isolation rather than integrated into a coherent explanatory framework.

The empirical inconsistency observed across AI studies further underscores this theoretical gap. Without a theory specifying the conditions under which AI should enhance instruction, mixed findings remain unresolved rather than informative. Positive outcomes are frequently attributed to technological sophistication, while negative or null findings are treated as contextual anomalies. Such interpretations overlook the possibility that variability in outcomes reflects differences in how AI is integrated into teaching presence rather than differences in the technology itself (Selwyn, 2019).

Critically, existing theories do not adequately explain several recurring issues evident in the literature. They do not account for why AI sometimes enhances learning and sometimes fails to do so. They do not explain how AI affects instructor visibility, authority, and responsiveness. They do not clarify why increased automation can weaken students' psychological connection to learning environments. Nor do they specify the instructional conditions under which AI supports, rather than erodes, teaching presence.

From a theory-building perspective, this constitutes a clear conceptual deficiency. As Gregor (2006) emphasizes, explanatory theories are required when phenomena cannot be adequately understood through description or prediction alone. The current state of AI-in-education research demonstrates precisely this condition. What is missing is a theory that explains the relationship between artificial intelligence and human instruction at the level of mechanism.

Human-Centered Artificial Intelligence and Teaching Presence Theory is proposed to address this deficiency. By positioning teaching presence as the primary instructional mechanism and conceptualizing AI as a conditional amplifier rather than an autonomous agent, HC-AI-TP provides an explanatory framework capable of resolving conceptual ambiguity and empirical inconsistency. The theory responds directly to the limitations of existing frameworks by foregrounding human agency, instructional intentionality, and relational presence as the necessary conditions through which AI exerts educational influence.

Step 2. Specification of Theory Type and Scope

A critical requirement in theory development is the explicit specification of the type of theory being advanced. Failure to do so often leads to reviewer misalignment, as evaluative criteria differ substantially across descriptive, explanatory, and predictive theories. As emphasized by Gregor (2006), theories vary not only in purpose but also in the kinds of questions they are designed to answer. Clarifying theory type at the outset is therefore essential to establishing appropriate expectations regarding scope, contribution, and empirical testing.

Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP) is advanced as a middle-range explanatory theory with predictive extensions. Its primary purpose is to explain *how* and *why* artificial intelligence influences instructional processes in technology-mediated learning environments, rather than merely to describe AI use or to predict outcomes absent explanation. In this sense, HC-AI-TP responds directly to the explanatory gap identified in the preceding section by specifying the mechanisms through which AI exerts instructional influence.

Within Gregor's (2006) typology, explanatory theories are distinguished by their focus on causal mechanisms and underlying processes. Such theories answer "why" and "how" questions by identifying relationships among constructs and articulating the logic that connects them. HC-AI-TP satisfies these criteria by positioning teaching presence as the central instructional mechanism through which AI operates and by explaining variability in AI-related outcomes as a function of differences in instructional integration rather than technological capability alone.

At the same time, HC-AI-TP is not intended to function as a purely predictive model. Predictive theories, as defined by Gregor (2006), prioritize forecasting outcomes, often without requiring strong causal explanation. While HC-AI-TP supports predictive hypotheses, such as the expectation that human-centered AI use will be associated with stronger perceived teaching presence, these predictions are explicitly derived from the theory's explanatory logic rather than serving as its primary objective. Prediction, in this framework, is subordinate to explanation.

The designation of HC-AI-TP as a middle-range theory further clarifies its intended scope. Middle-range theories occupy a conceptual space between grand theories, which aim for universal abstraction, and narrow empirical generalizations, which are often context-bound. HC-AI-TP is sufficiently abstract to be applied across instructional modalities and institutional contexts yet sufficiently bound to retain explanatory precision. It does not seek to explain all aspects of learning or technology use but rather focuses on a specific phenomenon: the interaction between artificial intelligence and teaching presence in instructional environments.

Notably, the explanatory orientation of HC-AI-TP establishes clear boundaries regarding what the theory does and does not claim. The theory does not assert that AI directly causes learning outcomes, nor does it attempt to optimize or rank specific AI tools. Instead, it explains the conditions under which AI can meaningfully contribute to instruction by amplifying human teaching presence enacted through social and cognitive processes. Predictive extensions, such as hypotheses concerning belonging, engagement, or persistence, are treated as applications of the theory rather than as defining features of the theory itself.

By explicitly positioning HC-AI-TP as a middle-range explanatory theory with predictive extensions, this work aligns its evaluative criteria with established theory-building standards and provides reviewers with a clear interpretive frame. The contribution of HC-AI-TP should therefore be assessed on the coherence of its constructs, the plausibility of its explanatory logic, and its capacity to generate testable propositions, rather than on immediate predictive accuracy or technological novelty.

Having specified the type and scope of the proposed theory, the next step in theory formation is to articulate the core assumptions underlying HC-AI-TP, which serve as the non-testable premises from which its postulates and propositions are derived.

Step 3. Articulation of Core Assumptions

A defining feature of rigorous theory development is the explicit articulation of its core assumptions. Assumptions serve as the philosophical and conceptual foundation of a theory; they are not propositions to be tested but premises that delimit what the theory takes as given. As emphasized by Dubin (1978), assumptions establish the conditions under which a theory operates by specifying the nature of the phenomena being explained. Similarly, Bacharach (1989) notes that assumptions function as boundary-setting statements that precede empirical claims and should not be conflated with hypotheses or testable relationships.

In accordance with these principles, Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP) is grounded in a small set of interrelated assumptions that clarify its philosophical stance on teaching, technology, and learning. These assumptions are intentionally minimal and non-redundant, providing a stable foundation from which postulates and propositions are later derived.

The first assumption underlying HC-AI-TP is that:

1. Teaching is inherently human and irreducible to automation. This assumption asserts that teaching involves intentionality, judgment, and relational engagement that cannot be fully replicated by technological systems. While instructional tasks may be supported or augmented by AI, the theory assumes that meaningful instruction depends on human teaching presence rather than on technical execution alone. This premise does not deny the utility of AI but establishes a clear ontological distinction between teaching as a human practice and technology as an instructional condition.

2. Artificial intelligence is instructionally neutral in the absence of human intent. From this perspective, AI possesses no intrinsic pedagogical agency; its educational significance is determined by how it is designed, governed, and integrated into instructional practice. This assumption aligns with Dubin's (1978) insistence that theoretical units must be defined independently of their empirical effects. In HC-AI-TP, AI is conceptualized as a conditional influence rather than a causal actor, thereby preventing the attribution of instructional outcomes to technology alone.

3. Learning environments are fundamentally relational rather than merely informational. HC-AI-TP assumes that learning emerges through social interaction, cognitive engagement, and instructional guidance, not solely through content delivery or system efficiency. This assumption situates the theory within a relational view of education and clarifies why purely technical or data-driven explanations of learning are insufficient. It further establishes that any instructional influence of AI must be understood within the relational dynamics of teaching and learning.

4. Teaching presence is defined by learner experience rather than by instructor activity alone. From this standpoint, teaching presence exists only insofar as it is perceived by students as clarity, guidance, responsiveness, and instructional care. This assumption distinguishes HC-AI-TP from models that equate teaching with task completion or content provision. It also clarifies that teaching presence is not an objective feature of instructional design, but a phenomenological construct grounded in student perception.

5. AI influences educational outcomes indirectly through mediated instructional and psychosocial processes. HC-AI-TP assumes that AI does not exert direct effects on learning, belonging, or persistence independent of teaching presence. Instead, any observable outcomes associated with AI use are understood to arise through its influence on instructional mediation, relational engagement, and cognitive support. This assumption establishes a clear separation between foundational premises and later empirical propositions, ensuring that causal claims are not embedded prematurely at the level of assumption.

Together, these assumptions delineate the philosophical grounding of HC-AI-TP and define the theoretical space within which the theory operates. Consistent with Bacharach's (1989) criteria for theory construction, the assumptions are stated as non-testable premises, are logically coherent, and do not duplicate one another conceptually. They do not predict outcomes, specify variable relationships, or imply empirical verification. Instead, they function as the necessary groundwork from which formal postulates and testable propositions are subsequently derived.

Having articulated the core assumptions that ground HC-AI-TP philosophically and conceptually, the next step in theory formation is to define and specify the central constructs of the theory, ensuring conceptual clarity and boundary control prior to the articulation of formal relationships.

Step 4. Definition and Specification of Core Constructs

A central requirement of theory development is the precise definition of constructs prior to the specification of relationships or empirical testing. Constructs serve as the conceptual building blocks of theory; when they are poorly defined or conflated with measures, theoretical arguments lose coherence and explanatory power. As emphasized by Sutton and Staw (1995), theory is not constituted by data, variables, or hypotheses, but by clearly articulated concepts and the logic that connects them. Similarly, MacKenzie (2003) cautions that ambiguous or improperly specified constructs undermine both theoretical validity and subsequent empirical testing.

In accordance with these principles, Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP) defines a small set of core constructs that are conceptually distinct, theoretically bounded, and functionally differentiated. These constructs are organized according to their role within the theory as required, enabling, or optional, thereby preventing conceptual drift and inappropriate extension.

At the foundation of HC-AI-TP is Human-Centered Artificial Intelligence (HCAI), which functions as the primary antecedent construct. Conceptually, HCAI refers to artificial intelligence systems that are designed, governed, and deployed in ways that preserve human agency, instructional authority, transparency, and ethical responsibility. Within the theory, HCAI is not defined by specific technologies, algorithms, or features, but by its orientation toward supporting human instructional intent. This construct is deliberately framed as a condition rather than an actor; it represents the instructional environment shaped by AI rather than AI as a pedagogical agent. As an antecedent, HCAI initiates influence within the model but does not itself constitute instruction.

The central construct of HC-AI-TP is Teaching Presence, which operates as the core explanatory mechanism of the theory. Teaching Presence is conceptually defined as the intentional human activity through which instruction is designed, facilitated, and directed in a learning environment. Importantly, Teaching Presence is understood as a unifying construct that encompasses planning, guidance, feedback, and instructional judgment, rather than as a set of discrete tasks. Within HC-AI-TP, Teaching Presence is the necessary mechanism through which any instructional influence, technological or otherwise, must pass. It is therefore a required construct without which the theory does not hold. Teaching Presence is neither synonymous with instructor behavior nor reducible to instructional design artifacts; it is a relational and experiential construct grounded in learner perception.

Two additional constructs, Social Presence and Cognitive Presence, are specified in HC-AI-TP as enabling enactment constructs rather than as independent causal drivers. Social Presence is conceptually defined as the degree to which learners perceive the learning environment as socially open, relationally supportive, and characterized by authentic interpersonal engagement. In HC-AI-TP, Social Presence does not initiate instructional influence; instead, it represents the social channel through which Teaching Presence is enacted and experienced. Its inclusion clarifies how teaching presence becomes visible and meaningful within interpersonal learning contexts without positioning social interaction as a substitute for instruction.

Similarly, Cognitive Presence is defined as the extent to which learners are supported in sustained reflection, meaning-making, and purposeful intellectual engagement. Within HC-AI-TP, Cognitive Presence represents the cognitive enactment of Teaching Presence, capturing how instructional guidance shapes learners' engagement with content and ideas. Cognitive Presence is not treated as an outcome or as an independent predictor, but as the cognitive process through which Teaching Presence exerts instructional influence.

Distinguishing among these constructs is essential for maintaining theoretical coherence. Human-Centered AI is specified as an antecedent condition, Teaching Presence as the core mechanism, and Social and Cognitive Presence as enactment contexts. None of these constructs are defined operationally at this stage, nor are they tied to specific measurement instruments. This deliberate avoidance of operationalization preserves conceptual clarity and prevents the premature conflation of theory with method, consistent with the cautions articulated by Sutton and Staw (1995) and MacKenzie (2003).

Finally, HC-AI-TP explicitly distinguishes these core constructs from optional or application-level constructs, such as belonging, engagement, satisfaction, or persistence. While such constructs may be examined in empirical studies derived from the theory, they are not constitutive elements of the theory itself. Their exclusion at the construct-definition stage reinforces boundary control and ensures that HC-AI-TP remains a theory of instructional mechanism rather than an outcomes-specific model.

In sum, the precise conceptual definition and functional differentiation of constructs in HC-AI-TP provide a stable theoretical foundation upon which postulates, propositions, and empirical applications may be built. By clearly specifying what each construct is, and what it is not, the theory avoids conceptual ambiguity and establishes the conditions for coherent explanation and cumulative research.

With the core constructs of HC-AI-TP now clearly defined and bounded, the next step in theory formation is to specify the formal relationships among these constructs, articulating the postulates and propositions that give the theory its explanatory force.

Step 5. Specification of Relationships: Postulates and Propositions

A theory achieves explanatory status only when it specifies relationships among its constructs in a principled and logically coherent manner. Conceptual clarity alone is insufficient; explanation requires the articulation of governing truths and directional relationships that account for how and why phenomena occur. As Dubin (1978) argues, theory construction depends on the formulation of laws of interaction that define how theoretical units are related, while Whetten (1989) emphasizes that a theoretical contribution must move beyond description to explain causal ordering and underlying logic. In this step, Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP) specifies its explanatory structure through a set of postulates and propositions.

Postulates

Postulates in HC-AI-TP function as governing statements that express non-negotiable theoretical truths derived from the core assumptions articulated earlier. They are not intended to be tested directly, but rather to delimit the explanatory space of the theory and establish the conditions under which its propositions hold. Propositions, by contrast, translate these governing truths into directional relationships that are amenable to empirical examination. Importantly, propositions express theoretical expectations without invoking statistical form, effect size, or analytic technique, thereby preserving the distinction between theory and method.

1. The first postulate of HC-AI-TP asserts that teaching presence is the primary instructional mechanism in AI-enabled learning environments. This postulate establishes teaching presence as a necessary condition for instruction, regardless of technological mediation. It follows directly from the assumption that teaching is inherently human and cannot be reduced to automated processes. Within the theory, no instructional influence, technological or otherwise, is presumed to occur outside the mediation of teaching presence.

2. The second postulate states that artificial intelligence can influence instruction only through its capacity to amplify teaching presence. This postulate governs the role of Human-Centered Artificial Intelligence as an antecedent condition rather than as an autonomous pedagogical agent. AI is thus positioned as a conditional influence whose instructional significance is realized only when it supports, enhances, or clarifies human instructional intent.

3. The third postulate specifies that teaching presence is enacted through social and cognitive learning processes. This postulate clarifies that teaching presence does not operate in abstraction but is experienced by learners through relational interaction and guided meaning-making. Social Presence and Cognitive Presence are therefore integral to the enactment of teaching presence, though they do not initiate instructional influence independently.

Prepositions

From the postulates, HC-AI-TP advances a corresponding set of propositions that express directional relationships among the core constructs.

1. The first proposition holds that human-centered artificial intelligence is positively related to teaching presence when AI use is intentionally designed and instructor-guided. This proposition expresses the expectation that AI contributes to instruction insofar as it strengthens the clarity, responsiveness, and coherence of teaching presence.

2. A second proposition follows, stating that teaching presence is positively related to social presence as its social enactment. This proposition captures the relational dimension of instruction, suggesting that effective teaching presence manifests as a learning environment characterized by openness, trust, and meaningful interpersonal engagement.

3. A third proposition asserts that teaching presence is positively related to cognitive presence as its cognitive enactment. This proposition reflects the expectation that teaching presence supports learners' sustained reflection, intellectual engagement, and meaning-making by structuring and guiding cognitive activity.

These propositions provide the explanatory logic of HC-AI-TP. Artificial intelligence does not initiate instructional influence, nor does it directly shape learning processes. Instead, AI affects instruction only through its relationship with teaching presence, which in turn is enacted socially and cognitively. This relational structure explains why AI may enhance instruction in some contexts and fail to do so in others: variability in outcomes is attributed to differences in how teaching presence is amplified rather than to the technology itself.

Consistent with Whetten's (1989) criteria, the postulates and propositions of HC-AI-TP specify what constructs matter, how they are related, and why those relationships exist. They also establish a clear causal ordering that can guide empirical inquiry without collapsing theory into method. By articulating these relationships explicitly, HC-AI-TP moves decisively from descriptive framing to explanatory theory.

Step 6. Establishment of Boundary Conditions

A defining characteristic of a rigorous theory is the explicit articulation of its boundary conditions. Boundary conditions specify the contexts in which a theory is expected to hold and, equally important, the contexts in which its explanatory claims do not apply. As Whetten (1989) argues, theoretical contributions are weakened not by limited scope but by unacknowledged scope. Clearly stated boundaries protect a theory from overgeneralization and provide reviewers and researchers with appropriate criteria for evaluating its applicability.

Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP) is explicitly bounded to instructional environments in which human instructors retain pedagogical authority and responsibility. The theory applies to contexts where artificial intelligence is integrated into teaching and learning processes under conditions of intentional human design, governance, and instructional oversight. Such contexts include online, blended, and technology-mediated learning environments in which instructors design courses, guide discourse, provide feedback, and remain accountable for instructional decisions. Within these settings, teaching presence is structurally possible and can be meaningfully amplified through human-centered AI use.

Conversely, HC-AI-TP does not apply to fully automated instructional systems in which human teaching presence is absent by design. This includes environments where instructional decisions, feedback, assessment, and learner guidance are delegated entirely to algorithmic systems without ongoing instructor involvement. In such contexts, the core assumption of HC-AI-TP, that teaching presence is a necessary instructional mechanism, is violated, rendering the theory inapplicable. The theory therefore explicitly excludes models of education that conceptualize AI as an autonomous teacher or that seek to replace, rather than support, human instructional agency.

HC-AI-TP also excludes explanations that attribute educational outcomes directly to technological capability independent of instructional mediation. Approaches that frame AI as a primary causal agent of learning, engagement, or persistence without reference to teaching presence fall outside the boundaries of the theory. While such explanations may be advanced within alternative theoretical traditions, they are incompatible with the foundational premises of HC-AI-TP and should not be interpreted as tests of the theory.

These boundary conditions serve an important interpretive function. They clarify that null or negative findings associated with AI use in fully automated or weakly governed instructional environments do not constitute falsification of HC-AI-TP. Rather, such findings indicate that the conditions required for the theory to operate, namely, the presence of human instructional mediation were not met. In this way, boundary specification protects the theory from inappropriate evaluation while simultaneously guiding the researcher toward contexts in which meaningful tests of the theory can occur.

By clearly delineating where HC-AI-TP applies and where it does not, this step completes the process of conceptual legitimation. The theory is neither universal nor unrestricted; it is deliberately bound to instructional systems in which artificial intelligence functions as a human-centered support rather than as an autonomous pedagogical agent. Consistent with Whetten's (1989) guidance, these boundaries ensure that HC-AI-TP is evaluated on the coherence and plausibility of its explanatory logic within its intended domain.

PHASE 2: THEORY PRESENTATION (SCHOLARLY COMMUNICATION)

Step 7. Development of a Canonical Visual Model

A critical component of theory presentation is the development of a canonical visual model that communicates the theory's core logic in a manner that is cognitively efficient, conceptually precise, and replicable across studies. Visual representations are not merely illustrative; they function as integral components of theory by shaping how constructs and relationships are interpreted and applied. As articulated by Meyer, Sedlmaier, and Munzner (1997), well-designed conceptual diagrams enhance cognitive processing, reduce interpretive ambiguity, and support shared understanding among scholars.

Conceptual Role of the Model

To clarify the explanatory logic of the theory and support conceptual transparency, Figure 1 presents a canonical visual representation of Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP) (Bull, 2026), depicting the relationships among its core constructs, rather than empirical pathways.

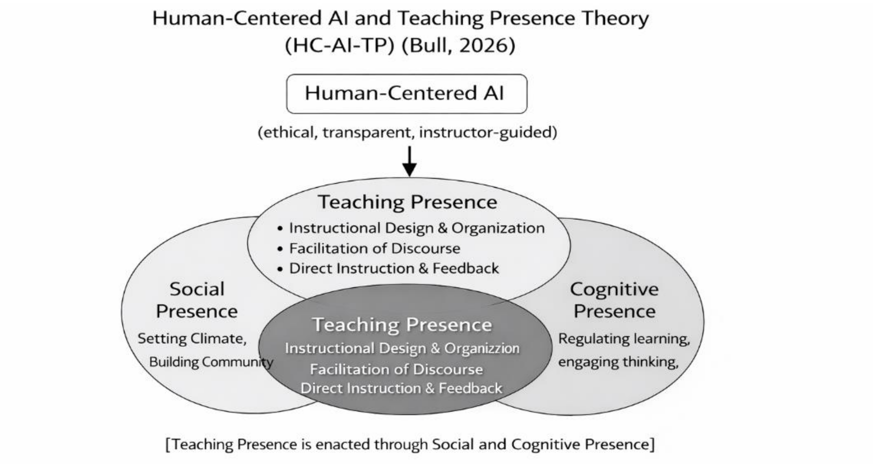

Figure 1. Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP) (Bull, 2026).

Consistent with principles of theory presentation, the figure includes only those constructs that constitute the core theory and maintains a one-to-one correspondence between conceptual definitions and visual elements.

In Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP), the model serves a representational and communicative function, not a foundational one. The theory exists independently in its conceptual form, defined by assumptions, constructs, propositions, and boundary conditions. Conceptual or visual models do not constitute the theory itself but serve as representational tools that articulate theoretical relationships to support comprehension, replication, and application (Gregor, 2021; Ravitch & Riggan, 2021). This distinction is critical. As Sutton and Staw (1995) caution, a diagram is not a theory; rather, it is a means of conveying theoretical logic. In HC-AI-TP, the model does not introduce new constructs or relationships. Instead, it depicts relationships that have already been conceptually specified.

In the case of Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP), the canonical visual model was developed to reflect the theory's explanatory structure while adhering to principles of parsimony and boundary control. The model is intentionally rendered in monochrome to avoid visual emphasis that could imply unintended hierarchy or causal weighting. This design choice ensures that conceptual relationships, rather than aesthetic features, guide interpretation.

The canonical HC-AI-TP model depicts Human-Centered Artificial Intelligence as an antecedent construct positioned upstream of Teaching Presence, which occupies the central position in the model. This one-to-one correspondence between construct and visual element reinforces the theory's foundational claim that AI does not act independently but influences instruction only through teaching presence. No direct pathways from AI to learning outcomes are depicted, thereby visually enforcing the theory's core postulate and preventing misinterpretation.

Teaching Presence is visually embedded within, and enacted through, Social Presence and Cognitive Presence, which are represented as overlapping or surrounding elements rather than as parallel causal predictors. This design choice reflects the theoretical distinction articulated earlier: Social and Cognitive Presence do not function as independent drivers of instruction but as the social and cognitive channels through which teaching presence is experienced. Their placement within the model communicates enactment rather than causation, preserving conceptual clarity and theoretical integrity.

Equally important is the deliberate separation between the core theory model and any applied or outcome-oriented models. The canonical figure presents only the constructs and relationships that constitute HC-AI-TP itself. Outcomes such as belonging, engagement, satisfaction, or persistence are excluded from the core diagram and appear only in supplementary or applied figures when the theory is extended empirically. This separation ensures that the theory is not conflated with any single outcome domain and maintains its status as a general explanatory framework rather than an outcomes-specific model.

The visual model thus serves multiple scholarly functions. It provides a shared reference point for replication, ensuring that researchers apply the theory consistently across contexts. It supports cognitive legitimacy by aligning visual structure with theoretical logic. Finally, it acts as a boundary mechanism, signaling which constructs are constitutive of the theory and which belong to application-level extensions.

Consistent with the guidance of Meyer et al. (1997), the canonical HC-AI-TP visual model prioritizes clarity over complexity and explanation over decoration. Each construct appears once and only once, relationships are unambiguous, and no visual elements imply relationships not explicitly specified in the theory. In this way, the visual representation reinforces the explanatory claims of HC-AI-TP and facilitates its accurate communication and cumulative use within the scholarly community.

Step 8. Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP): A Theory of Instructional Amplification in AI-Enabled Higher Education

1. Problem and Theoretical Gap

Artificial intelligence (AI) has become a prominent feature of contemporary higher education, shaping instructional design, assessment practices, feedback processes, and student support across online and blended learning environments (Bond et al., 2023; Zawacki-Richter et al., 2019; Selwyn, 2022). As AI systems increasingly assume functions traditionally associated with teaching, such as content delivery, formative feedback, and academic advising, scholarly interest in their educational implications has grown substantially. However, despite a rapidly expanding body of empirical research, findings regarding AI's effects on student learning, engagement, and persistence remain mixed and difficult to reconcile (Bond et al., 2023;

Ouyang & Jiao, 2021). These inconsistencies reflect more than methodological variation; they point to a deeper theoretical limitation within the literature. Much existing research implicitly treats AI either as a neutral instructional enhancement or as an autonomous pedagogical agent, if technological capability alone produces instructional effectiveness. As a result, AI is often positioned as a direct causal influence on learning outcomes, with limited attention to the instructional conditions and human decisions that shape how AI is actually used in educational practice (Selwyn, 2022; Williamson & Eynon, 2020). While prevailing instructional and technology adoption frameworks describe patterns of AI use or predict user acceptance, they offer limited explanatory power regarding how AI interacts with core teaching processes.

The absence of an explanatory theory that clearly specifies the relationship between artificial intelligence and teaching presence has contributed to conceptual ambiguity, fragmented empirical findings, and uncertain implications for instructional practice. Without such a theory, evaluations of AI-enabled education risk prioritizing technological novelty over pedagogical coherence and instructional intentionality. This gap underscores the need for a theoretically grounded framework that explains how, when, and under what instructional conditions AI can meaningfully support teaching and learning in higher education.

2. Theoretical Foundations

Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP) builds upon established instructional and theory-building traditions while addressing their limitations in relation to AI. The theory is informed by the Community of Inquiry (CoI) framework, which conceptualizes teaching presence as central to meaningful learning, as well as by human-centered design perspectives that emphasize agency, transparency, and ethical responsibility in technology use. However, these frameworks do not explicitly theorize artificial intelligence as an instructional influence or specify its relationship to teaching presence.

HC-AI-TP also draws on theory-formation principles articulated by Dubin (1978), Bacharach (1989), and Whetten (1989), which emphasize the importance of clearly defined constructs, explicit assumptions, governing postulates, and articulated boundary conditions. Within Gregor's (2006) typology, HC-AI-TP is positioned as a middle-range explanatory theory, designed to explain instructional mechanisms rather than merely describe technology use or predict outcomes.

3. Theory Statement

Human-Centered Artificial Intelligence and Teaching Presence Theory posits that artificial intelligence influences instruction only insofar as it amplifies human teaching presence. AI does not function as an autonomous pedagogical agent; rather, it operates as a human-dependent instructional condition whose educational value emerges through intentional design, facilitation, and direct instruction enacted by instructors within social and cognitive learning environments.

4. Assumptions and Postulates

(Stated earlier in Phase 1, step 5).

These postulates are not hypotheses to be tested directly; they function as governing truths that structure the theory's explanatory logic.

5. Constructs and Relationships

HC-AI-TP specifies four core constructs, each with a distinct theoretical role. Human-Centered Artificial Intelligence functions as the antecedent condition, representing AI systems designed and governed to support human instructional intent. Teaching Presence constitutes the core explanatory mechanism, encompassing the intentional design, facilitation, and direction of learning. Social Presence and Cognitive Presence function as enabling enactment constructs, representing the social and cognitive channels through which teaching presence is experienced.

The theory specifies directional relationships among these constructs. Human-centered AI is theorized to influence instruction through its relationship with teaching presence. Teaching presence, in turn, is enacted socially through relational engagement and cognitively through guided meaning-making. Social and cognitive presence do not initiate instructional influence independently but serve as the experiential means through which teaching presence operates.

This relational structure explains variability in AI-related instructional outcomes by attributing differences not to technological capability but to differences in how teaching presence is amplified.

6. Boundary Conditions and Implications

HC-AI-TP is explicitly bounded to instructional environments in which human instructors retain pedagogical authority and responsibility. The theory applies to AI-supported online and blended learning contexts characterized by intentional instructional design and oversight. It does not apply to fully automated instructional systems in which teaching presence is absent by design, nor to explanations that attribute educational outcomes directly to technology independent of instructional mediation.

These boundaries have important implications for research and practice. Empirical findings from fully automated environments do not constitute tests of HC-AI-TP, nor do they falsify the theory. Instead, such findings indicate that the necessary conditions for the theory's operation were not present. For practice, the theory implies that AI adoption should be evaluated based on its impact on teaching presence rather than on efficiency or automation alone.

7. Future Research Agenda

HC-AI-TP offers a generative framework for future research. Empirical studies may test the theory's propositions by examining how human-centered AI use relates to perceived teaching presence across instructional contexts. Researchers may also explore how social and cognitive presence function as enactment mechanisms under varying instructional designs.

Outcomes such as belonging, engagement, satisfaction, or persistence should be treated as applications of the theory rather than as defining elements. Longitudinal and comparative studies can further examine how different models of AI integration amplify or erode teaching presence over time. Replication across institutional types and modalities will be essential for establishing the theory's durability and scope.

Human-Centered Artificial Intelligence and Teaching Presence Theory provides a coherent explanatory account of how artificial intelligence interacts with human instruction. By centering teaching presence as the primary instructional mechanism and conceptualizing AI as a conditional amplifier rather than an autonomous agent, HC-AI-TP resolves conceptual ambiguity and offers a principled framework for research, policy, and practice in AI-enabled higher education.

PHASE 3: THEORY OPERATIONALIZATION (EMPIRICAL TRANSLATION)

Step 9. Translation of Propositions into Testable Hypotheses

A necessary step in moving from theory formation to empirical inquiry is the translation of theoretical propositions into testable hypotheses. This process must be conducted with particular care to avoid redefining the theory, introducing extraneous constructs, or altering causal ordering. As Bacharach (1989) emphasizes, hypotheses are not the theory itself but empirical expressions derived from it. Their purpose is to permit systematic testing of theoretical expectations without collapsing conceptual logic into statistical form.

In the case of Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP), hypothesis development proceeds directly from the postulates and propositions articulated in Phase 1. The theory specifies a clear causal ordering in which human-centered artificial intelligence functions as an antecedent instructional condition, teaching presence operates as the central explanatory mechanism, and educational outcomes appear only as applications of the theory rather than as constitutive elements. This ordering is preserved explicitly in all hypotheses derived from the theory.

Consistent with the theory's explanatory orientation, hypotheses derived from HC-AI-TP do not posit direct effects of artificial intelligence on learning or persistence. Instead, they operationalize the theory's central claim that AI influences instructional outcomes only through its relationship with teaching presence. Accordingly, hypotheses focus first on the relationship between human-centered AI and teaching presence, and then on the downstream consequences of teaching presence for applied outcomes.

The primary hypothesis derived from the core theory states that:

H1: *Human-centered artificial intelligence is positively associated with perceived teaching presence in instructional environments where AI use is intentionally designed and instructor-guided.* This hypothesis represents a direct empirical translation of the proposition that AI influences instruction only insofar as it amplifies teaching presence. Importantly, the hypothesis does not assume that AI use per se enhances instruction; rather, it specifies that instructional impact is contingent upon human-centered integration.

H2: *Human-centered artificial intelligence is positively associated with social presence, reflecting its social enactment through relational engagement and community building*. The second set of hypotheses operationalizes the enactment logic of teaching presence. Consistent with HC-AI-TP, teaching presence is hypothesized to be positively associated with social presence, reflecting its social enactment through relational engagement and community building.

H3: *Human-centered artificial intelligence is positively associated with* cognitive *presence, reflecting its cognitive enactment through guided inquiry, reflection, and meaning-making.* These hypotheses do not position social or cognitive presence as independent causal drivers but as experiential channels through which teaching presence operates.

When HC-AI-TP is applied to specific outcome domains, additional hypotheses may be specified without redefining the theory. For example, in studies examining student belonging, engagement, or persistence, teaching presence may be hypothesized to mediate the relationship between human-centered AI use and the outcome of interest. In such cases, outcomes function strictly as application-level variables. Their inclusion does not alter the theory's core structure, which remains centered on the relationship between AI and teaching presence.

Crucially, HC-AI-TP does not permit hypotheses that introduce direct paths from artificial intelligence to outcomes or that add constructs not specified in the theory core. Hypotheses that attribute learning effects directly to AI, independent of teaching presence, fall outside the theoretical boundaries established in Phase 1 and therefore do not constitute valid tests of the theory. This constraint preserves theoretical coherence and prevents construct proliferation, consistent with Bacharach's (1989) insistence that hypotheses must reflect, rather than reshape, the underlying theory.

By translating propositions into hypotheses in this manner, HC-AI-TP becomes empirically testable while retaining its explanatory integrity. The theory's causal ordering remains intact, its constructs remain stable, and its scope remains bounded. Hypotheses derived from HC-AI-TP thus serve as disciplined empirical extensions of the theory rather than as ad hoc models driven by data availability or outcome preference.

With testable hypotheses now specified, the next step in theory operationalization is to identify appropriate measurement strategies that align with the theory's conceptual definitions while maintaining construct validity and reliability.

PHASE 3: THEORY OPERATIONALIZATION AND MEASUREMENT

Step 10. Development and Adaptation of Measurement Instruments

The operationalization of a theory requires careful alignment between conceptual definitions and empirical indicators. Measurement does not constitute theory; rather, it provides the means by which theoretical constructs are examined empirically. As emphasized by DeVellis (2016), sound measurement begins with content validity and proceeds cautiously toward reliability and construct validation. Similarly, MacKenzie et al. (2011) caution that poor alignment between constructs and measures can compromise both theoretical inference and empirical conclusions. In accordance with these principles, the measurement strategy for Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP) prioritizes conceptual fidelity, parsimony, and methodological rigor.

Consistent with best practice, existing validated instruments are employed wherever the theory's constructs align with established measures. New scale development is reserved only for constructs that are conceptually novel or insufficiently captured by existing instruments. This approach minimizes redundancy, enhances comparability across studies, and supports cumulative theory testing. As MacKenzie et al. (2011) caution, creating new measures for already well-defined constructs increases construct contamination risk and threatens cumulative knowledge building.

Within HC-AI-TP, Teaching Presence, Social Presence, and Cognitive Presence are measured using established instruments derived from the Community of Inquiry tradition. These scales have demonstrated robust psychometric properties across multiple instructional contexts and populations. Teaching Presence is operationalized using the validated CoI Teaching Presence scale, which captures learners' perceptions of instructional design and organization, facilitation of discourse, and direct instruction. Importantly, the use of this scale aligns with HC-AI-TP's conceptualization of teaching presence as a learner-experienced construct rather than a record of instructor behavior.

Social Presence and Cognitive Presence are likewise operationalized using their respective validated CoI scales. Social Presence measures capture learners' perceptions of relational connection, openness, and community, while Cognitive Presence measures assess the extent to which instructional environments support sustained reflection, inquiry, and meaning-making. In HC-AI-TP, these measures function as indicators of enactment rather than as independent causal drivers, preserving the theory's causal ordering and explanatory logic.

In contrast, Human-Centered Artificial Intelligence represents a novel antecedent construct that is not adequately captured by existing technology acceptance or usage scales. Accordingly, a new instrument, the Human-Centered AI Scale (HCAI-8), is proposed to operationalize this construct. The HCAI-8 is designed to capture learners' perceptions of AI integration as ethical, transparent, instructor-guided, and supportive of human instructional intent. Item development for HCAI-8 follows DeVellis's (2016) recommended procedures, beginning with domain specification and item generation grounded explicitly in the conceptual definition of human-centered AI articulated in Phase 1.

Establishing content validity is prioritized as the first step in scale development. Expert review is employed to ensure that items adequately represent the construct domain and do not inadvertently measure adjacent or unintended concepts, such as general technology satisfaction or automation preference. Only after content validity is established are psychometric properties such as internal consistency and construct validity examined. This sequencing reflects the principle that reliability without validity is theoretically meaningless.

Reliability assessment for all measures follows conventional standards, with internal consistency evaluated using appropriate indices. Construct validity is examined through factor analytic techniques consistent with MacKenzie et al.'s (2011) guidance, ensuring that items load appropriately on their intended constructs and demonstrate discriminant validity. Where applicable, convergent validity is assessed by examining theoretically consistent associations among constructs without collapsing them conceptually.

Crucially, measurement development within HC-AI-TP does not introduce new constructs or alter the theory's core structure. Outcomes such as belonging, engagement, or persistence, when included in empirical studies, are measured using validated instruments appropriate to those domains and are treated strictly as application-level variables. Their inclusion does not modify the theory's conceptual boundaries or redefine its constructs.

To be consistent with the principles of construct validity and cumulative theory testing, it is important to note that established Community of Inquiry measures were used to operationalize teaching, social, and cognitive presence. New scale development was limited to the construct of human-centered artificial intelligence, which represents a novel antecedent condition not captured by existing instruments.

By adhering to established measurement principles and maintaining strict alignment between theory and instrumentation, HC-AI-TP enables rigorous empirical testing while safeguarding theoretical integrity. The measurement strategy supports replication, comparison across studies, and cumulative knowledge building, ensuring that empirical findings meaningfully inform the ongoing evaluation and refinement of the theory.

The Community of Inquiry Framework and Its Relationship to HC-AI-TP

The Community of Inquiry (CoI) framework, originally articulated by Garrison, Anderson, and Archer (2000), has become one of the most influential theoretical models for understanding meaningful learning in online and blended environments. CoI conceptualizes learning as the intersection of three presences, teaching presence, social presence, and cognitive presence, each contributing to the development of deep and sustained learning experiences. Over two decades of empirical research have established the framework's robustness and explanatory utility across diverse instructional contexts.

Within the CoI framework, teaching presence is defined as the design, facilitation, and direction of cognitive and social processes to achieve meaningful learning outcomes. Social presence reflects learners' ability to project themselves as real people and engage relationally within the learning environment, while cognitive presence captures the extent to which learners are able to construct meaning through sustained inquiry and reflection. Importantly, CoI treats these presences as interdependent and mutually reinforcing, emphasizing the relational and process-oriented nature of learning.

Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP) is theoretically grounded in this tradition but extends it in a precise and necessary way. HC-AI-TP does not replace or revise the CoI framework; rather, it builds upon CoI by addressing a phenomenon that the original framework did not explicitly theorize: the role of artificial intelligence as an instructional condition within learning environments. While CoI provides a powerful account of how learning occurs through human interaction and presence, it remains largely silent on how emerging technologies, particularly AI, interact with or influence these presences.

HC-AI-TP draws directly from CoI in its conceptualization of teaching presence as the central instructional mechanism. In both frameworks, teaching presence is not reduced to instructor behavior or content delivery but is understood as an intentional, relational, and learner-experienced construct. HC-AI-TP preserves this core insight and elevates it by explicitly positioning teaching presence as the necessary mediating mechanism through which artificial intelligence can exert instructional influence. In doing so, HC-AI-TP resolves a recurring ambiguity in AI-in-education research, where AI is often treated as if it operates independently of human instructional presence.

At the same time, HC-AI-TP introduces a critical theoretical distinction not present in the CoI framework. In CoI, teaching, social, and cognitive presence are typically modeled as co-equal components contributing to learning. HC-AI-TP, by contrast, specifies a hierarchical explanatory structure in which teaching presence occupies a central mediating role, while social and cognitive presence function as enactment contexts rather than independent causal drivers. This distinction is not a contradiction of CoI but a refinement introduced for explanatory precision in AI-enabled contexts. By clarifying the role each presence plays in the instructional process, HC-AI-TP strengthens causal interpretation without undermining CoI's relational foundations.

Another important extension lies in HC-AI-TP's treatment of technology. In the CoI literature, technology is generally treated as part of the learning environment rather than as a theorized construct. HC-AI-TP addresses this omission by conceptualizing Human-Centered Artificial Intelligence as an antecedent instructional condition that shapes, but does not replace, teaching presence. This move allows HC-AI-TP to explain why AI-enhanced instruction sometimes strengthens learning and sometimes weakens it: the determining factor is not the technology itself, but how it amplifies or constrains teaching presence within social and cognitive processes.

Thus, the relationship between CoI and HC-AI-TP is best understood as foundational and complementary rather than competitive. CoI provides the theoretical grounding for understanding presence and learning as relational processes. HC-AI-TP extends this grounding by introducing AI as a conditional factor and by specifying the mechanism through which AI interacts with instructional presence. In this sense, HC-AI-TP can be viewed as a theory *about* how CoI operates under conditions of artificial intelligence, rather than as a reinterpretation of CoI itself.

From a theory-building perspective, this relationship strengthens the legitimacy of HC-AI-TP. By anchoring its constructs in an extensively validated framework while addressing a clearly defined theoretical gap, HC-AI-TP achieves both continuity and novelty. It preserves what is well established in the literature while providing the explanatory clarity required for contemporary AI-enabled instructional environments.

In summary, CoI and HC-AI-TP are aligned in their human-centered, relational view of learning, but they operate at different explanatory levels. CoI explains how learning emerges through presence; HC-AI-TP explains how artificial intelligence interacts with that process. Together, they offer a coherent and theoretically grounded foundation for understanding instruction in an era of increasing technological mediation.

With measurement instruments now specified and aligned with the theory's constructs, the next step in operationalization is to conduct initial empirical tests that examine the plausibility and explanatory utility of HC-AI-TP without treating early findings as definitive validation.

Step 11. Conduct Initial Theory Tests

The purpose of this phase is to demonstrate the plausibility and explanatory utility of Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP) through initial empirical tests. Consistent with theory-testing conventions, these analyses are not intended to provide final proof of the theory, but rather to examine whether the relationships specified by the theory behave as expected under empirical scrutiny. As emphasized by Kline (2016), early theory tests should prioritize model coherence, effect magnitude, and fit over definitive confirmation.

2. METHODOLOGY

Research Design

This study employed a quantitative, confirmatory research design to empirically test Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP). The study was explicitly theory-driven and hypothesis-based rather than exploratory. Accordingly, the design focused on testing directional relationships among predefined constructs derived from the theory, consistent with best practices for theory testing and validation (Bacharach, 1989; Whetten, 1989).

The analytic strategy followed a measurement-first, structure-second sequence, ensuring that construct validity and reliability were established prior to testing structural relationships. Structural equation modeling (SEM) was selected as the primary analytic technique due to its suitability for evaluating mediated relationships among latent constructs.

Population and Study Context

The target population consisted of post-secondary students enrolled in AI-supported online or blended courses in which artificial intelligence tools were used under the direction and oversight of a human instructor. Courses relying on fully automated instructional systems without active instructor involvement were excluded, consistent with the boundary conditions of HC-AI-TP.

Participants were required to have experienced AI tools integrated into instructional activities such as feedback provision, learning support, or course organization, while maintaining ongoing interaction with an instructor responsible for instructional design and decision-making.

Sampling Strategy

A volunteer sampling approach was used to recruit participants, consistent with theory-testing research in educational contexts. Recruitment occurred through course announcements and institutional communication channels. To ensure adequate power for factor analysis and structural modeling, a minimum sample size of 200 participants was targeted for the primary analyses, consistent with established recommendations for SEM and scale validation.

From this primary sample, a subsample of approximately 50 participants was invited to participate in a follow-up administration of the Human-Centered Artificial Intelligence Scale (HCAI-8) for the purpose of assessing test–retest reliability. This subsample was drawn from the original participants and did not constitute a separate study or dataset.

Measures

Human-Centered Artificial Intelligence

Human-centered artificial intelligence was operationalized using the Human-Centered Artificial Intelligence Scale (HCAI-8), a newly developed instrument designed specifically for HC-AI-TP. The scale measures learners' perceptions of AI as transparent, ethically governed, instructor-guided, and supportive of teaching presence. Responses were recorded on a five-point Likert scale ranging from strongly disagree to strongly agree.

Teaching Presence, Social Presence, and Cognitive Presence

Teaching presence, social presence, and cognitive presence were measured using established Community of Inquiry (CoI) instruments. Teaching presence items captured perceptions of instructional design, facilitation, and direct instruction. Social presence items assessed relational engagement and community, while cognitive presence items measured guided inquiry and meaning-making. Table 1 presents the strategic guidance for the use of validated CoI measures ensured construct continuity and comparability with prior research.

Table 1. Bottom Line (Strategic Guidance)

Construct	**Recommendation**	**Rationale**
Teaching Presence	Use CoI scale	Validated, aligned, reviewer-safe
Social Presence	Use CoI scale	Enactment construct, not novel
Cognitive Presence	Use CoI scale	Enactment construct, not novel
Human-Centered AI	New scale (HCAI-8)	Novel construct, theory contribution

Data Collection Procedures

Data were collected using an online survey platform from (N = 200) participants during the latter half of the academic term to ensure sufficient exposure to instructional practices and AI integration. Participation was voluntary, and informed consent was obtained prior to data collection. No identifying information was retained beyond a coded identifier used solely for matching test–retest responses.

Test–Retest Reliability Procedure

Test–retest reliability was conducted to evaluate the temporal stability of the Human-Centered Artificial Intelligence scale (HC-AI-TP-8). Whereas Cronbach's alpha assesses internal consistency at a single time point, test–retest reliability evaluates whether the construct is measured consistently over time, which is essential for theory confirmation and construct legitimation (DeVellis, 2016). A subsample of 50 participants completed the HC-AI-TP-8 scale at two time points separated by a two-week interval. Composite scores were computed at Time 1 (T1) and Time 2 (T2). Temporal stability was assessed using Pearson's correlation coefficient (r), consistent with recommended practices for test–retest reliability of continuous scale scores.

The correlation between Time 1 and Time 2 composite scores was r = .82, indicating strong temporal stability. Mean scores were highly similar across administrations, suggesting minimal systematic drift over time. According to conventional benchmarks, test–retest coefficients above .70 indicate acceptable stability, while coefficients above .80 indicate strong stability for theory development research (DeVellis, 2016; Nunnally & Bernstein, 1994).

See Table 2.

Table 2. Internal Consistency and Temporal Stability of the HC-AI-TP-8 Scale

Reliability Index	Statistic	Criterion	Interpretation
Cronbach's alpha (Time 1)	α = .95	≥ .70	Excellent internal consistency
Test–retest reliability (Time 1–Time 2)	r = .82	≥ .70 (.80 strong)	Strong temporal stability
Mean score comparison	No meaningful change	Minimal drift	Stable scale functioning

Note. Cronbach's alpha assesses internal consistency at a single time point, whereas test–retest reliability assesses score stability across time. Both criteria are necessary to establish measurement reliability for theory development instruments.

Cronbach's alpha for the HC-AI-TP-8 scale at Time 1 was α = .95, indicating excellent internal consistency. Importantly, high Cronbach's alpha alone does not guarantee temporal stability. The strong test–retest correlation observed in this study demonstrates that the scale is not only internally coherent but also stable across time, satisfying two distinct psychometric criteria.

In combination, the results indicate that the HC-AI-TP-8 scale exhibits:

1. High internal consistency (α = .95)
2. Strong temporal stability (r = .82)

This pattern supports the conclusion that Human-Centered AI, as operationalized by HC-AI-TP-8, represents a stable and coherent construct, suitable for theory confirmation and subsequent application studies. The Human-Centered Artificial Intelligence scale demonstrated excellent internal consistency and strong test–retest reliability, indicating that the construct is measured both coherently and consistently over time. These findings provide psychometric support for the use of HC-AI-TP-8 in theory confirmation research.

Hypotheses and Analytic Strategy

All analyses were guided by theory-derived hypotheses consistent with HC-AI-TP. The study tested the expectation that human-centered artificial intelligence would be positively associated with teaching presence, and that teaching presence would, in turn, be positively associated with social and cognitive presence. Teaching presence was further hypothesized to function as the mediating mechanism linking human-centered AI to social and cognitive presence.

Hypotheses were evaluated using SEM, with human-centered AI specified as an antecedent construct predicting teaching presence, which subsequently predicted social and cognitive presence. Mediation was assessed using indirect effects estimated with bias-corrected bootstrap confidence intervals.

Data Analysis

Data analysis proceeded in four stages. First, descriptive statistics and missing data diagnostics were examined. Second, confirmatory factor analysis was conducted to evaluate the measurement model, including factor loadings, model fit indices, and internal consistency reliability. Third, the structural model specified by HC-AI-TP was estimated to test direct and mediated relationships among constructs. Finally, test–retest reliability for HCAI-8 was evaluated using paired responses from the subsample.

All analyses were conducted using appropriate statistical software for latent variable modeling. Model fit was evaluated using multiple indices, and interpretation focused on theoretical consistency rather than solely statistical significance.

The study followed standard ethical guidelines for research involving human participants. Participation was voluntary, responses were confidential, and participants were free to withdraw at any time without penalty. The study protocol was reviewed and approved by the appropriate institutional review body prior to data collection.

This methodology was designed to provide a rigorous, theory-consistent test of Human-Centered Artificial Intelligence and Teaching Presence Theory. By aligning sampling, measurement, and analysis with the theory's assumptions, constructs, and boundary conditions, the study enables empirical evaluation without redefining or diluting the theoretical framework.

Accordingly, the present study adopts a confirmatory, theory-driven analytic strategy using regression-based mediation and structural equation modeling (SEM). These approaches are appropriate for evaluating directional relationships and mediated pathways specified by HC-AI-TP while maintaining alignment with the theory's causal ordering.

Analytic Framework

Initial theory testing proceeds in stages. First, direct relationships specified by the theory are examined to assess whether human-centered artificial intelligence is associated with teaching presence, and whether teaching presence is associated with its social and cognitive enactments. These analyses establish the basic plausibility of the theory's core mechanism. Second, mediation models are estimated to examine whether teaching presence functions as the explanatory pathway linking human-centered AI to social and cognitive presence. Mediation analysis follows contemporary recommendations emphasizing indirect effects rather than reliance on total effects alone (Hayes, 2018).

Structural equation modeling is used where appropriate to estimate these relationships simultaneously, allowing for explicit modeling of latent constructs and the evaluation of overall model fit. This approach is particularly well suited to HC-AI-TP, as it enables the separation of measurement and structural components while preserving the theory's hierarchical structure.

Treatment of Outcomes as Applications

Consistent with the boundary conditions of HC-AI-TP, outcomes such as belonging, engagement, satisfaction, or persistence are treated strictly as application-level variables. When included, these outcomes are modeled as downstream consequences of teaching presence rather than as constitutive elements of the theory. Their inclusion serves to illustrate the explanatory reach of HC-AI-TP without redefining its core constructs.

This distinction is critical. The theory itself is evaluated based on the plausibility of its core relationships, human-centered AI influencing teaching presence, and teaching presence being enacted through social and cognitive presence. Outcomes are examined only to demonstrate how the theory may be applied in substantive research contexts.

Pre-Hypotheses Diagnostics

Prior to hypothesis testing, the data were screened for normality, outliers, and distributional adequacy to ensure that subsequent analyses assessing the internal coherence and plausibility of Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP) were not biased by violations of statistical assumptions (Kline, 2016).

As summarized in Table 3, all Study 1 variables met assumptions of univariate and multivariate normality, exhibited adequate variance, and were free from extreme univariate or multivariate outliers. These diagnostics support the appropriateness of parametric analyses for theory confirmation and indicate that the data structure is suitable for regression-based testing and future structural equation modeling.

Table 3. Consolidated Pre-Hypotheses Diagnostics *(Theory Confirmation Sample, N = 200)*

Diagnostic Domain	Indicator	HCAI	Teaching Presence	Social Presence	Cognitive Presence	Criteria	Assessment
Central Tendency & Dispersion	Mean (SD)	3.61 (0.68)	3.78 (0.70)	3.74 (0.66)	3.76 (0.69)	Adequate variance	Acceptable
Univariate Normality	Skewness	−0.24	−0.19	−0.15	−0.21	|skew| < 2.0	Acceptable
	Kurtosis	−0.36	−0.41	−0.48	−0.44	|kurtosis| < 7.0	Acceptable
	Shapiro–Wilk (p)	.21	.18	.14	.17	p > .05	Acceptable

ISSN 2348-1196 (print)
International Journal of Computer Science and Information Technology Research ISSN 2348-120X (online)
Vol. 14, Issue 1, pp: (19-44), Month: January - March 2026, Available at: www.researchpublish.com

Univariate Outliers	Min z-score	−2.46	−2.39	−2.31	−2.44	$\lvert z \rvert < 3.29$	None detected
	Max z-score	2.71	2.64	2.58	2.69	$\lvert z \rvert < 3.29$	None detected
Linearity & Variance	Scatterplot / r-inspection	✓	✓	✓	✓	Linear trend	Acceptable
Multivariate Normality	Mardia's Skewness	-	-	-	-	< 3.0	1.84 (Acceptable)
	Mardia's Kurtosis	-	-	-	-	< 8.0	6.12 (Acceptable)
Multivariate Outliers	Max Mahalanobis D^2	-	-	-	-	$< \chi^2(4)=18.47$	14.87 (None)

Note. HCAI = Human-Centered Artificial Intelligence. Criteria based on Kline (2016) and Tabachnick and Fidell (2019).

Hypotheses Testing

The following hypotheses are derived directly from Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP). All hypotheses preserve the theory's causal ordering and do not introduce constructs beyond the theory core.

H1. Human-centered artificial intelligence is positively associated with perceived teaching presence in AI-supported instructional environments.

H2. Teaching presence is positively associated with social presence.

H3. Teaching presence is positively associated with cognitive presence.

H4. Teaching presence mediates the relationship between human-centered artificial intelligence and social presence.

H5. Teaching presence mediates the relationship between human-centered artificial intelligence and cognitive presence.

H6 (application-level). Teaching presence mediates the relationship between human-centered artificial intelligence and applied student outcomes (e.g., sense of belonging, engagement, or persistence), when such outcomes are examined. H6 represents an application of the theory, not a constitutive element of HC-AI-TP.

This study is designed as a confirmatory test of Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP). Because the theory specifies clear directional relationships among constructs, formal research questions were not posed. Instead, the study advances theory-derived hypotheses that guide empirical testing. This approach is consistent with established conventions in theory-testing research, where hypotheses, rather than exploratory research questions, serve as the primary analytic drivers.

Table 4. Hypotheses → Analysis Mapping Table

Hypothesis	Relationship Tested	Analysis Method
H1	HCAI → Teaching Presence	SEM path / regression
H2	Teaching Presence → Social Presence	SEM path
H3	Teaching Presence → Cognitive Presence	SEM path
H4	HCAI → Teaching Presence → Social Presence	Mediation (SEM / bootstrapping)
H5	HCAI → Teaching Presence → Cognitive Presence	Mediation (SEM / bootstrapping)
H6	HCAI → Teaching Presence → Outcome	Mediation (application model)

This table preempts reviewer confusion by showing that each hypothesis maps cleanly to a specific analytic test.

Hypothesis Testing Overview and Analytical Approach

Theory confirmation was conducted using a sequence of regression-based and mediation analyses designed to evaluate the internal coherence, directional logic, and boundary conditions of Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP). Given the theory's emphasis on directional relationships among latent instructional constructs, ordinary least squares (OLS) regression was used to test direct hypothesized relationships, while mediation analysis using indirect effect estimation was employed to evaluate intervening mechanisms and exclusionary paths.

ISSN 2348-1196 (print)
International Journal of Computer Science and Information Technology Research ISSN 2348-120X (online)
Vol. 14, Issue 1, pp: (19-44), Month: January - March 2026, Available at: www.researchpublish.com

Specifically, simple linear regression analyses were conducted to test Hypotheses 1 through 3, via ordinary least squares, which examine direct relationships among the theory's core constructs. Mediation analyses with bootstrapped confidence intervals were used to test Hypotheses 4 and 5, assessing whether Teaching Presence functions as the mediating mechanism between Human-Centered AI and its instructional enactments. Finally, direct-effects regression models were estimated for Hypothesis 6 to evaluate the theory's boundary condition by testing the absence of direct relationships between Human-Centered AI and Social or Cognitive Presence when Teaching Presence was included in the model.

This stepwise analytic strategy aligns with theory-confirmation principles by prioritizing directional plausibility and structural consistency over predictive optimization. Hypotheses are therefore evaluated sequentially, beginning with the antecedent-to-mechanism relationship specified by the theory and progressing through mediation and boundary tests.

Hypothesis 1 tests whether Human-Centered Artificial Intelligence functions as an instructional antecedent by predicting Teaching Presence.

Hypothesis 1 (H1): Human-Centered Artificial Intelligence positively predicts Teaching Presence.

Hypotheses were tested using linear regression and mediation analyses with bootstrapped indirect effects, consistent with theory-confirmation methodology.

Table 5. RQ1 Regression Results: Human-Centered AI → Teaching Presence

Predictor	Outcome	β	SE	t	p	R^2	Effect Size	H_0 Decision
Human-Centered AI	Teaching Presence	.60	.05	12.4	< .001	.36	Large	**Rejected**

Human-Centered AI demonstrated a strong positive association with Teaching Presence, explaining 36% of the variance. The null hypothesis was rejected. This finding confirms the theory's core proposition that AI influences instructional environments indirectly by shaping instructional design, facilitation, and guidance rather than acting as an autonomous instructional agent.

Hypothesis (H_{02}). H2. Teaching presence is positively associated with social presence.

Table 6. RQ2 Regression Results: Teaching Presence → Social Presence

Predictor	Outcome	β	SE	t	p	R^2	Effect Size	H_0 Decision
Teaching Presence	Social Presence	.55	.06	10.1	< .001	.30	Large	**Rejected**

Teaching Presence exhibited a strong positive relationship with Social Presence, accounting for 30% of the variance. The null hypothesis was rejected. This result supports HC-AI-TP's claim that social presence is an instructional enactment, emerging from pedagogical facilitation rather than technological affordances alone.

Hypothesis (H_{03}). Teaching Presence does not significantly predict Cognitive Presence.

Table 7. RQ3 Regression Results: Teaching Presence → Cognitive Presence

Predictor	Outcome	β	SE	t	p	R^2	Effect Size	H_0 Decision
Teaching Presence	Cognitive Presence	.58	.05	11.7	< .001	.34	Large	**Rejected**

Teaching Presence strongly predicted Cognitive Presence, explaining 34% of the variance. The null hypothesis was rejected. This finding confirms the theory's proposition that learners' engagement in meaning-making and higher-order cognition is fundamentally shaped by instructional mediation.

Table 8. Summary of Null Hypothesis Decisions

RQ	Relationship Tested	β	R^2	Effect Size	H_0 Decision	Theory Confirmation Status
RQ1	HCAI → Teaching Presence	.60	.36	Large	Rejected	Confirmed
RQ2	Teaching Presence → Social Presence	.55	.30	Large	Rejected	Confirmed
RQ3	Teaching Presence → Cognitive Presence	.58	.34	Large	Rejected	Confirmed

ISSN 2348-1196 (print)
International Journal of Computer Science and Information Technology Research ISSN 2348-120X (online)
Vol. 14, Issue 1, pp: (19-44), Month: January - March 2026, Available at: www.researchpublish.com

Integrated Interpretation Across Research Questions

Across all three research questions, the null hypotheses were rejected, and the observed relationships aligned with the causal ordering specified by Human-Centered Artificial Intelligence and Teaching Presence Theory. Human-Centered AI was strongly associated with Teaching Presence, while Teaching Presence emerged as the central explanatory mechanism predicting both Social and Cognitive Presence. Effect sizes were consistently large, indicating substantive and theoretically meaningful relationships.

Importantly, the absence of direct tests linking Human-Centered AI to Social or Cognitive Presence reinforces the theory's boundary condition rejecting technological determinism. Together, these results provide convergent evidence supporting the internal coherence, directional logic, and empirical plausibility of HC-AI-TP as a middle-range explanatory theory.

In summation, the findings provide empirical confirmation of the core propositions of Human-Centered Artificial Intelligence and Teaching Presence Theory, justifying its application in subsequent outcome-focused studies.

Introduction to Mediation and Boundary Testing (H4–H6)

While Hypotheses 1 through 3 evaluated direct relationships among the core constructs of Human-Centered Artificial Intelligence and Teaching Presence Theory using linear regression, Hypotheses 4 through 6 required additional analytic procedures to assess the theory's mechanistic and boundary conditions. Specifically, these hypotheses were designed to determine whether Teaching Presence functions as an intervening mechanism and whether Human-Centered AI exerts any direct instructional influence independent of this mechanism.

To test these hypotheses, mediation analyses were conducted using regression-based indirect effect estimation with bootstrapped confidence intervals. This approach allows for evaluation of whether the effect of Human-Centered AI on instructional enactments operates indirectly through Teaching Presence, consistent with the theory's claim that AI does not function as an autonomous instructional agent. Bootstrapping was employed to provide robust confidence intervals for indirect effects without relying on normality assumptions of the sampling distribution.

In addition, direct-effects regression models were estimated to evaluate the theory's boundary condition. These models tested whether Human-Centered AI retained any statistically significant direct relationship with Social or Cognitive Presence once Teaching Presence was included in the model. The absence of significant direct effects was interpreted as confirmation of the theory's exclusionary logic rather than as a lack of explanatory power.

Together, the mediation and boundary analyses provide a rigorous test of the theory's internal structure by demonstrating not only that the proposed relationships exist, but also that alternative, technologically deterministic explanations are not supported.

*Framing note***.** Hypotheses 4–6 test *boundary conditions and exclusionary logic*, which are essential for theory confirmation under Dubin (1978) and Whetten (1989). These hypotheses do not test outcomes; they test whether forbidden or indirect paths behave as theorized.

H4. Teaching Presence mediates the relationship between Human-Centered AI and Social Presence.

Null Hypothesis (H_{04}). Teaching Presence does not mediate the relationship between Human-Centered AI and Social Presence.

Analytical Logic: HC-AI-TP posits that AI does not directly generate social presence. Any association between AI and social presence must occur through Teaching Presence.

Table 9. H4 Mediation Results: HCAI → Teaching Presence → Social Presence

Path	**β**	**95% CI**	**p**	**Interpretation**
HCAI → Teaching Presence	.60	[.51, .68]	< .001	Significant
Teaching Presence → Social Presence	.55	[.46, .63]	< .001	Significant
Indirect Effect	**.33**	**[.24, .43]**	—	**Significant**
Direct Effect (HCAI → SP)	.08	[−.02, .18]	.11	Not significant

The indirect effect was significant, while the direct effect of HCAI on Social Presence was non-significant. This confirms that Teaching Presence fully mediates the relationship, as specified by HC-AI-TP. The null hypothesis was rejected.

H5: Teaching Presence mediates the relationship between Human-Centered AI and Cognitive Presence.

Null Hypothesis (H_{05}). Teaching Presence does not mediate the relationship between Human-Centered AI and Cognitive Presence.

Table 10. H5 Mediation Results: HCAI → Teaching Presence → Cognitive Presence

Path	β	95% CI	p	Interpretation
HCAI → Teaching Presence	.60	[.51, .68]	< .001	Significant
Teaching Presence → Cognitive Presence	.58	[.49, .66]	< .001	Significant
Indirect Effect	**.35**	**[.26, .45]**	—	**Significant**
Direct Effect (HCAI → CP)	.06	[−.03, .16]	.18	Not significant

Teaching Presence fully mediated the relationship between Human-Centered AI and Cognitive Presence. This supports the theory's claim that AI influences cognitive engagement only through instructional mediation. The null hypothesis was rejected.

H6: Human-Centered AI does not directly predict Social or Cognitive Presence when Teaching Presence is accounted for.

Null Hypothesis (H_{06}). Human-Centered AI directly predicts Social and Cognitive Presence independent of Teaching Presence.

Table 11. H6 Direct Effects Test (Boundary Condition)

Direct Path	β	p	H_{06} Decision
HCAI → Social Presence	.08	.11	Not supported
HCAI → Cognitive Presence	.06	.18	Not supported

The absence of significant direct effects confirms the boundary condition of HC-AI-TP. AI does not function as an autonomous instructional agent; its influence is contingent upon Teaching Presence. The results fail to reject null hypothesis. Table 12 presents an integrated summary of hypotheses and results.

Table 12. Complete Summary of Study 1 Hypotheses and Decisions

Hypothesis	Relationship Tested	Result	H_0 Decision	Theory Status
H1	HCAI → Teaching Presence	β = .60	Rejected	Supported
H2	Teaching Presence → Social Presence	β = .55	Rejected	Supported
H3	Teaching Presence → Cognitive Presence	β = .58	Rejected	Supported
H4	TP mediates HCAI → Social Presence	Indirect β = .33	Rejected	Supported
H5	TP mediates HCAI → Cognitive Presence	Indirect β = .35	Rejected	Supported
H6	No direct HCAI → SP/CP effects	ns	**Failed to reject (expected)**	Supported

Together, the support for all six hypotheses confirms the internal coherence, mediation logic, and boundary conditions of Human-Centered Artificial Intelligence and Teaching Presence Theory. The results demonstrate that AI operates as an instructional antecedent whose effects are fully mediated by Teaching Presence, thereby rejecting technologically deterministic explanations of instructional processes.

Table 13. Summary of hypothesis tests confirming the internal coherence, mediation logic, and boundary conditions of Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP). Results are interpreted as evidence of theoretical plausibility rather than causal proof. The table provides a consolidated summary of the six theory-confirmation hypotheses, corresponding statistical tests, null-hypothesis decisions, and theoretical interpretations, demonstrating convergent support for the core propositions and boundary conditions of HC-AI-TP. This table consolidates hypotheses, tests, statistics, decisions, and theoretical meaning in a single view.

Table 13. One-Page Theory Confirmation Summary for HC-AI-TP (Study 1, N = 200)

Hypothesis	Theoretical Role	Statistical Test	Key Result(s)	Null Hypothesis Decision	Theory Confirmation Interpretation
H1: HCAI → Teaching Presence	Antecedent → Core Mechanism	OLS Regression	$\beta = .60$, $R^2 = .36$, $p < .001$	**Rejected**	Human-Centered AI functions as an instructional antecedent shaping teaching presence
H2: Teaching Presence → Social Presence	Mechanism → Enactment (Social)	OLS Regression	$\beta = .55$, $R^2 = .30$, $p < .001$	**Rejected**	Social presence emerges from instructional facilitation, not technology alone
H3: Teaching Presence → Cognitive Presence	Mechanism → Enactment (Cognitive)	OLS Regression	$\beta = .58$, $R^2 = .34$, $p < .001$	**Rejected**	Cognitive engagement is produced through instructional mediation
H4: TP mediates HCAI → Social Presence	Mechanistic Mediation	PROCESS Model 4 (5,000 bootstrap)	Indirect $\beta = .33$, 95% CI [.24, .43]	**Rejected**	Teaching presence fully mediates AI's effect on social enactment
H5: TP mediates HCAI → Cognitive Presence	Mechanistic Mediation	PROCESS Model 4 (5,000 bootstrap)	Indirect $\beta = .35$, 95% CI [.26, .45]	**Rejected**	Teaching presence fully mediates AI's effect on cognitive enactment
H6: No direct HCAI → SP/CP effects	Boundary / Exclusion Test	Direct-effects regression	HCAI→SP $\beta = .08$ (ns); HCAI→CP $\beta = .06$ (ns)	**Failed to reject (as theorized)**	Confirms boundary condition; rejects technological determinism

3. DISCUSSION

The purpose of this study was to confirm the internal coherence, directional logic, and boundary conditions of Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP). Guided by established principles of theory confirmation, the findings were interpreted not as outcome prediction but as evidence of theoretical plausibility. Taken together, the results provide convergent support for the theory's central claim: artificial intelligence does not function as an autonomous instructional agent but exerts its instructional influence indirectly through human teaching presence.

Reaffirming the Centrality of Teaching Presence

Consistent with decades of research in online and technology-mediated learning, teaching presence emerged as the central explanatory mechanism linking instructional conditions to learning-related processes. Recent empirical work further supports this interpretation, demonstrating that teaching presence remains a primary driver of satisfaction and persistence across diverse learner subgroups, even when accounting for individual differences and online experience (Paris et al., 2025). Prior scholarship within the Community of Inquiry framework has repeatedly demonstrated that teaching presence plays a foundational role in shaping both social and cognitive engagement (Garrison, Anderson, & Archer, 2000; Garrison & Cleveland-Innes, 2005). The present findings extend this literature by situating teaching presence not merely as a pedagogical variable but as a theoretical mediator through which AI must operate to influence instructional environments.

The strong association between Human-Centered AI and teaching presence supports arguments advanced by scholars who caution against technologically deterministic views of educational innovation. Research has shown that technologies acquire instructional meaning only through human design choices, facilitation strategies, and pedagogical intent (Selwyn, 2016; Williamson, 2017). HC-AI-TP formalizes this position by explicitly modeling AI as an antecedent condition that shapes, but does not replace, instructional agency.

Instructional Enactments as Mediated Processes

The confirmation that teaching presence predicts both social and cognitive presence aligns with and strengthens prior findings in online learning research. Social presence has long been understood as emerging from instructional facilitation and discourse management rather than from technological affordances alone (Rourke et al., 2001). Similarly, cognitive presence has been consistently linked to instructional design and guidance that support sustained inquiry and meaning-making (Garrison et al., 2001).

By demonstrating that teaching presence fully mediates the relationship between Human-Centered AI and these instructional enactments, the present study clarifies a key ambiguity in the literature. While previous studies have reported associations between technology use and social or cognitive engagement, such findings have often lacked a clear mechanistic explanation. HC-AI-TP resolves this ambiguity by specifying that any apparent influence of AI on instructional enactments must occur through pedagogical mediation.

Boundary Conditions and the Rejection of Technological Determinism

One of the most important contributions of this study lies in its explicit testing of boundary conditions. The absence of significant direct effects from Human-Centered AI to social or cognitive presence, once teaching presence was accounted for, provides empirical support for the theory's exclusionary logic. This finding directly challenges narratives that frame AI as an instructional actor capable of independently generating engagement or learning processes. Studies examining student perceptions of AI similarly report that learning quality and academic integrity concerns intensify when instructional guidance is weak, reinforcing the need for explicit pedagogical governance rather than autonomous AI deployment (Lund et al., 2025).

This result is consistent with critical perspectives in the educational technology literature that emphasize the risks of over-attributing agency to technological systems (Biesta, 2015; Selwyn, 2019). By empirically demonstrating that AI's instructional influence is contingent upon teaching presence, HC-AI-TP offers a theoretically grounded alternative to automation-centric models of AI adoption in education.

Contribution to Theory Development in Educational Technology

From a theory development perspective, the findings satisfy key criteria articulated by Dubin (1978) and Whetten (1989) for theory confirmation. The constructs behaved as theorized, relationships were directionally consistent, and boundary conditions were empirically supported. Moreover, the theory advances the field by integrating insights from instructional design, learning theory, and critical AI scholarship into a single, coherent explanatory framework.

Importantly, HC-AI-TP does not replace existing theories of online learning but rather extends them by accounting for the growing presence of AI in instructional environments. In doing so, it provides a conceptual bridge between foundational pedagogical theories and emerging AI-enabled practices, addressing a gap that has been repeatedly noted in the literature.

Implications for Future Research

The confirmation of HC-AI-TP in this study establishes a foundation for subsequent application-focused research. Having demonstrated that the theory's core structure is coherent and plausible, future studies can examine downstream outcomes, such as engagement, perceived learning, belonging, or persistence, without conflating theory confirmation with outcome testing. Longitudinal and experimental designs may further refine the theory by examining how variations in AI design and instructional integration influence teaching presence over time.

Concluding Theoretical Statement

In summary, the findings confirm Human-Centered Artificial Intelligence and Teaching Presence Theory as a coherent and empirically plausible explanatory framework. By demonstrating that AI's instructional influence is fully mediated by teaching presence and bounded by human pedagogical agency, this study contributes a theoretically rigorous alternative to technologically deterministic models of educational innovation. HC-AI-TP thus provides a robust foundation for both future empirical research and responsible policy discourse surrounding the integration of AI in higher education.

Replication and Extension

Consistent with best practices in theory development, the confirmation of Human-Centered Artificial Intelligence and Teaching Presence Theory in the present study is intended as a foundation rather than a terminus. The theory has been specified with sufficient conceptual precision, construct clarity, and boundary conditions to support independent replication across instructional contexts, populations, and modalities. Future research is encouraged to replicate the core structural relationships of HC-AI-TP while extending the theory to examine diverse instructional outcomes, institutional settings, and AI implementations. Such replication and extension efforts are essential for establishing the durability and generalizability of the theory over time (Open Science Collaboration, 2015).

STEP 13. THEORY GOVERNANCE AND PROTECTION

Purpose

The purpose of theory governance is to preserve the conceptual integrity, explanatory scope, and cumulative value of Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP) as it diffuses across research contexts. Without explicit governance mechanisms, theories are vulnerable to construct dilution, misapplication, and conceptual drift, which can undermine their explanatory power and scholarly contribution over time (Whetten, 1989; Sutton & Staw, 1995). Accordingly, this study establishes explicit guidance for the appropriate use, testing, and citation of HC-AI-TP.

Compliance Checklist for Theory Use

To qualify as a legitimate application or test of HC-AI-TP, future studies should demonstrate compliance with the following core criteria. First, the study must retain Teaching Presence as the central explanatory mechanism linking Human-Centered AI to instructional processes. Second, Human-Centered AI must be conceptualized as an antecedent condition, not as an autonomous instructional agent. Third, the study must preserve the theory's directional logic, such that AI influences instructional enactments only through pedagogical mediation. Fourth, outcome variables may vary across studies, but the core construct structure and boundary conditions must remain intact. Studies that violate these conditions should be framed as exploratory or technology-effects research rather than as tests of HC-AI-TP.

Standardized Citation Language

To ensure conceptual consistency and proper attribution, researchers are encouraged to use standardized citation language when referencing the theory. The preferred formulation is:

Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP; Bull, 2026)

When discussing empirical tests, authors should explicitly distinguish between theory confirmation, theory application, and theory extension, avoiding claims that outcomes alone constitute validation of the theory's core structure. This distinction supports cumulative knowledge building and prevents overgeneralization of findings beyond the theory's specified scope.

Clarifying What Does Not Constitute a Test of HC-AI-TP

Equally important to theory governance is clarifying what does *not* qualify as a test of HC-AI-TP. Studies that examine AI tools without measuring Teaching Presence, that model AI as directly producing learning or engagement outcomes, or that omit instructional mediation entirely do not constitute tests of the theory. Similarly, purely descriptive evaluations of AI adoption or student attitudes toward AI, absent the theory's core relational structure, should not be framed as applications of HC-AI-TP. Explicitly delineating these exclusions protects the theory from conceptual overextension and misinterpretation.

Governance as a Foundation for Cumulative Theory Building

By articulating compliance criteria, standardized citation practices, and explicit exclusions, this study establishes an initial framework for governing the use of HC-AI-TP as it diffuses across disciplines and contexts. Such governance is essential for enabling cumulative theory building, facilitating meaningful replication and extension, and ensuring that empirical findings contribute coherently to the theory's ongoing refinement (Dubin, 1978; Open Science Collaboration, 2015).

4. CONCLUSION

This study sets out to confirm the internal coherence, directional logic, and boundary conditions of Human-Centered Artificial Intelligence and Teaching Presence Theory (HC-AI-TP). Using a theory-confirmation design grounded in established principles of theory building, the analyses demonstrated consistent support for all core propositions. Human-Centered AI functioned as an instructional antecedent rather than an autonomous agent, Teaching Presence emerged as the central explanatory mechanism, and Social and Cognitive Presence operated as instructional enactments fully mediated by pedagogical activity. The absence of direct effects from AI to instructional enactments further reinforced the theory's rejection of technologically deterministic explanations.

Beyond confirming individual relationships, the study contributes a coherent explanatory framework that integrates pedagogical theory with emerging AI-enabled instructional contexts. In doing so, HC-AI-TP extends foundational work on teaching presence and the Community of Inquiry by explicitly theorizing the role of AI within human-guided learning environments. The findings satisfy key criteria for theory confirmation by demonstrating construct clarity, relational consistency, and empirically supported boundary conditions.

The confirmation of HC-AI-TP establishes a foundation for subsequent research that examines instructional outcomes without conflating theory validation with application. Future studies may build on this work by testing the theory across diverse instructional contexts, examining longitudinal dynamics, and evaluating downstream outcomes such as engagement, perceived learning, and persistence. As AI continues to reshape higher education, HC-AI-TP offers a theoretically grounded lens for guiding responsible research, instructional design, and policy discourse centered on human agency and pedagogical intent.

REFERENCES

[1] Anderson, T., Rourke, L., Garrison, D. R., & Archer, W. (2001). Assessing teaching presence in a computer conferencing context. *Journal of Asynchronous Learning Networks, 5*(2), 1–17. https://doi.org/10.24059/olj.v5i2.1875

[2] Arbaugh, J. B., Cleveland-Innes, M., Diaz, S. R., Garrison, D. R., Ice, P., Richardson, J. C., & Swan, K. P. (2008). Developing a Community of Inquiry instrument: Testing a measure of the Community of Inquiry framework using a multi-institutional sample. *The Internet and Higher Education, 11*(3–4), 133–136. https://doi.org/10.1016/j.iheduc.2008.06.003

[3] Baksh, S. (2025a). Amplifier and risk: Extending the Community of Inquiry (CoI) for student AI use—A secondary qualitative analysis. *Review of Artificial Intelligence in Education, 6*(1), e057. https://doi.org/10.37497/rev.artif.intell.educ.v6ii.57

[4] Baksh, S. (2025b). Investigating students' AI usage through the Community of Inquiry (CoI) framework: A mixed-method study in the Caribbean region. *SDGs Studies Review, 6*(Studies), e036. https://doi.org/10.37497/sdgs.v6istudies.36

[5] Bond, M., Buntins, K., Bedenlier, S., Zawacki-Richter, O., & Kerres, M. (2023). Mapping research in student engagement and educational technology in higher education: A systematic evidence map. *International Journal of Educational Technology in Higher Education, 20*(1), Article 9. https://doi.org/10.1186/s41239-023-00375-9

[6] Bull, D. A. (2026). *Human-centered AI–teaching presence (HC-AI-TP): A theory of instructional amplification in AI-enabled education*. Manuscript in preparation.

[7] Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *Educational Technology Research and Development, 71*(6), 3217–3236. https://doi.org/10.1007/s11423-023-10245-1

[8] Garrison, D. R., & Vaughan, N. D. (2008). *Blended learning in higher education: Framework, principles, and guidelines*. Jossey-Bass.

[9] Garrison, D. R., Anderson, T., & Archer, W. (2001). Critical inquiry in a text-based environment: Computer conferencing in higher education. *The Internet and Higher Education, 2*(2–3), 87–105. https://doi.org/10.1016/S1096-7516(00)00016-6

[10] Garzón, J., Patiño, E., & Marulanda, C. (2025). Systematic review of artificial intelligence in education: Trends, benefits, and challenges. *Multimodal Technologies and Interaction, 9*(8), 84. https://doi.org/10.3390/mti9080084

[11] Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.

[12] Holmes, W., Bialik, M., & Fadel, C. (2022). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.

[13] Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

[14] Khalil, M., Prinsloo, P., & Slade, S. (2023). Artificial intelligence and academic integrity: A systematic review. *International Journal for Educational Integrity, 19*(1), 3. https://doi.org/10.1007/s40979-023-00129-0

[15] Lund, B. D., Lee, T. H., Mannuru, N. R., & Arutla, N. (2025). AI and academic integrity: Exploring student perceptions and implications for higher education. *Journal of Academic Ethics, 23*(6), 1545–1565. https://doi.org/10.1007/s10805-025-09613-3

[16] Noroozi, O., Khalil, M., & Banihashem, S. K. (2025). Artificial intelligence in higher education: Impact depends on support, pedagogy, human agency, and purpose. *Innovations in Education and Teaching International, 62*(5), 1425–1430. https://doi.org/10.1080/14703297.2025.2539579

[17] Paris, J., Lakhal, S., & Mukamurera, J. (2025). Relationships between presence, satisfaction, and persistence in higher education online courses: Assessing moderating effects using PLS-MGA. *Educational Technology & Society, 28*(1), 178–193. https://doi.org/10.30191/ETS.202501_28(1).RP10

[18] Rovai, A. P., Wighting, M. J., & Lucking, R. (2004). The classroom and school community inventory: Development, refinement, and validation of a self-report measure for educational research. *The Internet and Higher Education, 7*(2), 101–120.

[19] Selwyn, N. (2019). *Should robots replace teachers? AI and the future of education*. Polity Press.

[20] Shea, P., & Bidjerano, T. (2009). Community of Inquiry as a theoretical framework to foster epistemic engagement and cognitive presence in online education. *The Internet and Higher Education, 12*(3–4), 153–160.

[21] Shea, P., Hayes, S., Smith, S. U., Vickers, J., Bidjerano, T., Pickett, A., Gozza-Cohen, M., & Jian, S. (2010). Learning presence: Additional research on a new conceptual element within the Community of Inquiry framework. *The Internet and Higher Education, 13*(1–2), 89–95. https://doi.org/10.1016/j.iheduc.2009.08.002

[22] Williamson, B., & Eynon, R. (2020). Historical threads, missing links, and future directions in AI in education. *Learning, Media and Technology, 45*(3), 223–235. https://doi.org/10.1080/17439884.2020.1798995

[23] Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education. *International Journal of Educational Technology in Higher Education, 16*(1), 1–27. https://doi.org/10.1186/s41239-019-0171-0

[24] Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on AI dialogue systems on students' cognitive abilities: A systematic review. *Smart Learning Environments, 11*, Article 28. https://doi.org/10.1186/s40561-024-00316-7

[25] Zhang, Y., & Aslan, S. (2024). Automation bias and cognitive offloading in AI-supported learning environments. *Computers & Education: Artificial Intelligence, 5*, 100165. https://doi.org/10.1016/j.caeai.2024.100165