MODESTUM
EURASIA Journal of Mathematics, Science and Technology Education, 2026, 22(10), em2931
ISSN:1305-8223 (online)
OPEN ACCESS
Research Paper
https://doi.org/10.29333/ejmste/19421

A preliminary machine presence measure within the community of inquiry framework: How students perceive AI-mediated guidance in multivariable calculus course

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Received 21 July 2026 ▪ Accepted 06 September 2026

Abstract

The integration of generative artificial intelligence (AI) into mathematics learning raises a foundational question for the community of inquiry (CoI) framework: do students perceive guidance provided by an AI tutor as distinguishable from guidance associated with a human teacher (teaching presence), or do they treat the two as interchangeable? This study pursued two aligned aims: (1) to develop and provide an initial psychometric evaluation of a five-item machine presence measure, including a direct test of its perceived distinctiveness from teaching presence; and (2) to examine how perceived machine presence is associated with learner presence and cognitive presence. In a cross-sectional survey of 211 undergraduates who used an AI tutor configured to provide Socratic guidance rather than direct solutions in a multivariable calculus course, the measurement model showed good fit ($\chi^2/df = 1.65$, CFI = 0.960, TLI = 0.951, RMSEA = 0.056, SRMR = 0.042) and adequate convergent validity (machine presence average variance extracted = 0.596, composite reliability = 0.880). Machine and teaching presence showed discriminant validity (HTMT = 0.49; Fornell-Larcker criterion satisfied), and a competing-models comparison showed that the two-factor solution was statistically preferable to the one-factor solution ($\Delta\chi^2$ (1) = 310.9, $p < 0.001$; CFI = 0.963 vs. 0.660). Perceived machine presence was positively associated with learner presence ($\beta = 0.62$) and cognitive presence ($\beta = 0.34$), and learner presence with cognitive presence ($\beta = 0.49$); the indirect association via learner presence was significant, consistent with the hypothesized mediation model. Importantly, when the paths from machine and teaching presence to learner and cognitive presence were constrained to equality, model fit did not deteriorate ($\Delta\chi^2$ (2) = 0.539, $p = 0.764$), consistent with a source-attribution interpretation in which students distinguish the agent of guidance while perceiving comparable pedagogical functions. We interpret these results as evidence of perceptual and measurement-level distinctness within one particular AI-tutoring implementation, and we emphasize that measurement separability does not by itself establish that machine presence constitutes a new, functionally independent theoretical dimension of the CoI framework. Given the cross-sectional, single-group, single-context, self-report design, all structural findings are interpreted associationally rather than as evidence of instructional effectiveness or causal direction.

Keywords: machine presence, community of inquiry, scale development, initial psychometric evaluation, learner presence, cognitive presence, AI-supported mathematics learning

This study is part of an ongoing research project examining the integration of AI into mathematics education through an extension of the CoI framework.

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Contribution to the literature

- This study extends the community of inquiry (CoI) framework by empirically establishing machine presence as a distinct construct.
- It clarifies the theoretical role of AI within AI-supported learning environments. It develops and validates a measurement instrument for machine presence.
- It identifies learner presence as an important mechanism linking machine presence and cognitive presence. It shows the pedagogical potential of AI-mediated Socratic guidance in mathematics education.

INTRODUCTION

The integration of generative artificial intelligence (AI) into digital mathematics education is prompting a fundamental rethinking of established teaching and learning paradigms (Chen et al., 2020; Hwang & Tu, 2021). For more than two decades, the CoI framework has served as a dominant model for understanding learning in online and blended environments, locating meaningful educational experience in the dynamic interaction of cognitive presence, social presence, and teaching presence (Garrison et al., 2000; Swan et al., 2009). These three elements have traditionally been conceptualized as human-driven processes grounded in interactions among instructors and learners.

Contemporary AI systems unsettle this human-centered assumption. Unlike earlier educational technologies that functioned largely as passive tools, generative AI can produce immediate, context-sensitive feedback, guide students through problem-solving sequences, and shape the trajectory of knowledge construction in ways that resemble instructional functions (Holmes et al., 2019; Luckin et al., 2016; Zawacki-Richter et al., 2019). As the boundary between human and technological roles blurs, a specific theoretical question arises: should AI be positioned as an independent epistemic presence within the learning community, or as a technologically mediated extension of teaching presence? Recent scholarship has gestured toward a "machine presence" to capture the active role of AI agents (Kim et al., 2020; Smutny & Schreiberova, 2020), yet this notion remains conceptually suggestive. It has rarely been operationalized into a measurable construct, and its empirical separability from teaching presence has not been tested.

It is important to be precise from the outset about what a positive separability result can, and cannot, establish. Demonstrating that students distinguish guidance coming from an AI system from guidance coming from a teacher is not the same as demonstrating that these are two different educational presences. An equally plausible interpretation is that students distinguish who provides the guidance—the source or agent—while the underlying pedagogical function (diagnostic feedback, hinting, decomposition, conceptual focusing) remains essentially the same as that long attributed to teaching presence. The present study is designed to adjudicate the first, perceptual question; it is not designed, and does not claim, to settle the second, stronger question of functional or theoretical independence. We return to this distinction throughout.

This question is especially consequential in mathematics. Mathematical learning depends on structured reasoning, conceptual abstraction, and iterative problem solving (Alam & Mohanty, 2024; Hwang & Tu, 2021; Mukherjee, 2025; Nakakoji & Wilson, 2020). AI systems that generate complete solutions can inadvertently bypass precisely these processes, reducing opportunities for exploration and weakening intellectual autonomy (Nopas, 2025; Varghese, 2025; Yavich, 2025). Mathematics education therefore offers a critical setting for examining how AI reshapes cognitive engagement and inquiry. A persistent gap also exists between the intended design of educational technologies and their actual use (Cai, 2024; Selwyn, 2010): learners frequently interact with systems in unanticipated ways, including attempts to elicit direct answers from tools meant to scaffold reasoning.

To foreground inquiry rather than answer delivery, the present study situates learning in an AI environment deliberately constrained to provide Socratic guidance—probing questions, strategic hints, and reflective prompts—rather than worked solutions. For example, when students approached partial derivatives, the system asked which variable was being differentiated and which held constant; for double integrals, it prompted students to interpret the region defined by the bounds. Within this perspective, the value of AI guidance is expected to depend not only on system design but also on learners' capacity to regulate their own learning, captured by learner presence (Chang et al., 2023; Shea & Bidjerano, 2010).

Accordingly, and to keep the research design aligned with the claims it can support, this study pursues two aims. First, it develops and provides an initial psychometric evaluation of a measure of machine presence, including an explicit empirical test of whether students perceive machine presence as distinguishable from teaching presence. Second, it examines how perceived machine presence is associated with learner presence and cognitive presence. The second aim is framed associationally: the cross-sectional, single-group design does not permit claims about the instructional effectiveness of the AI, and no such claims are advanced. The study contributes

(1) a documented, preliminarily evaluated instrument for perceived machine presence,

(2) an explicit test of whether students perceive AI-mediated scaffolding as distinct from instructor teaching presence, together with an honest appraisal of what such a perceptual result does and does not establish, and

(3) evidence on how perceived AI scaffolding co-varies with self-regulated and cognitive engagement in mathematics, foregrounding the role of learner presence.

We deliberately position these contributions as an initial operationalization of how students perceive AI-mediated instructional guidance within one particular learning environment, rather than as the establishment of a new theoretical dimension of the CoI framework.

THEORETICAL FRAMEWORK

The Community of Inquiry

The CoI framework explains how meaningful learning is constructed through collaborative interaction within a learning community, particularly in online and blended contexts (Cleveland-Innes, 2019; Garrison et al., 2000). Grounded in social constructivism, it holds that knowledge is not passively transmitted but actively constructed through dialogue, reflection, and the negotiation of meaning (Du Preez & West, 2022). Meta-analytic evidence links the CoI presences to learning outcomes across diverse settings (Martin et al., 2022), establishing the framework as a robust foundation for analyzing technology-enhanced learning.

The Three Original Presences

Cognitive presence refers to learners' capacity to construct and confirm meaning through sustained reflection and discourse, typically enacted across the phases of triggering events, exploration, integration, and resolution (Garrison et al., 2000). Social presence denotes the ability of individuals to present themselves authentically within the community, fostering the trust, openness, and cohesion that support collaboration (Swan et al., 2009). Teaching presence encompasses the design, facilitation, and direction of learning—including discourse management and the provision of cognitive scaffolding—so as to realize intended outcomes (Arbaugh et al., 2008; Garrison, 2007). Teaching presence is the construct against which perceived machine presence must be discriminated, because both concern the guidance of inquiry.

Learner Presence

Extending the original triad, Shea and Bidjerano (2010) proposed learner presence to capture students' self-regulation and metacognitive engagement—goal setting, monitoring, and the strategic control of effort and learning activities. Learner presence is theoretically central in AI-supported settings, where learners must decide how to use, interrogate, or resist algorithmic guidance; recent work on AI chatbots similarly emphasizes self-regulated learning as a mechanism of effective use (Chang et al., 2023).

Machine Presence and the Distinctiveness Problem

Building on emerging discussions of AI as a non-human participant (Kim et al., 2020), we define machine presence as learners' *perception* of the AI's capacity to provide structured, non-answer-giving guidance—probing questions, strategic hints, and reflective prompts—that sustains their reasoning. This definition deliberately excludes the social-affective and course-design functions that are central to teaching presence. The conceptual proximity of the two constructs, however, makes their empirical separability an open question rather than an assumption: if learners cannot distinguish AI scaffolding from instructor teaching presence, perceived machine presence collapses into teaching presence.

It is essential to be explicit about the two rival interpretations that a discriminant result can receive, because they are frequently conflated. Under the first, distinct-presence interpretation, learners perceive AI-mediated guidance as a qualitatively different kind of educational presence, warranting an additional element within the CoI framework. Under the second, source-attribution interpretation, learners perceive one and the same pedagogical function—guidance of inquiry—but attribute it to a different agent (an algorithm rather than a human), so that what is "distinct" is the source, not the function. Both interpretations predict that machine and teaching presence items will separate into two factors and satisfy discriminant-validity criteria. A competing-models comparison and HTMT can therefore establish that learners do not treat the two sets of items as interchangeable indicators of a single latent variable, but such evidence cannot, on its own, distinguish between these two interpretations. Adjudicating between them would require evidence beyond measurement separation, for example, demonstrating that machine and teaching presence have differential nomological relations with other constructs, that machine presence predicts outcomes incrementally over teaching presence, or that the two respond differently to experimental manipulation. The present study provides the measurement-separability evidence and interprets it accordingly; it treats the stronger, functional-distinctiveness question as a matter for future research. This reasoning provides the rationale for the competing-models analysis reported below and disciplines the claims we draw from it.

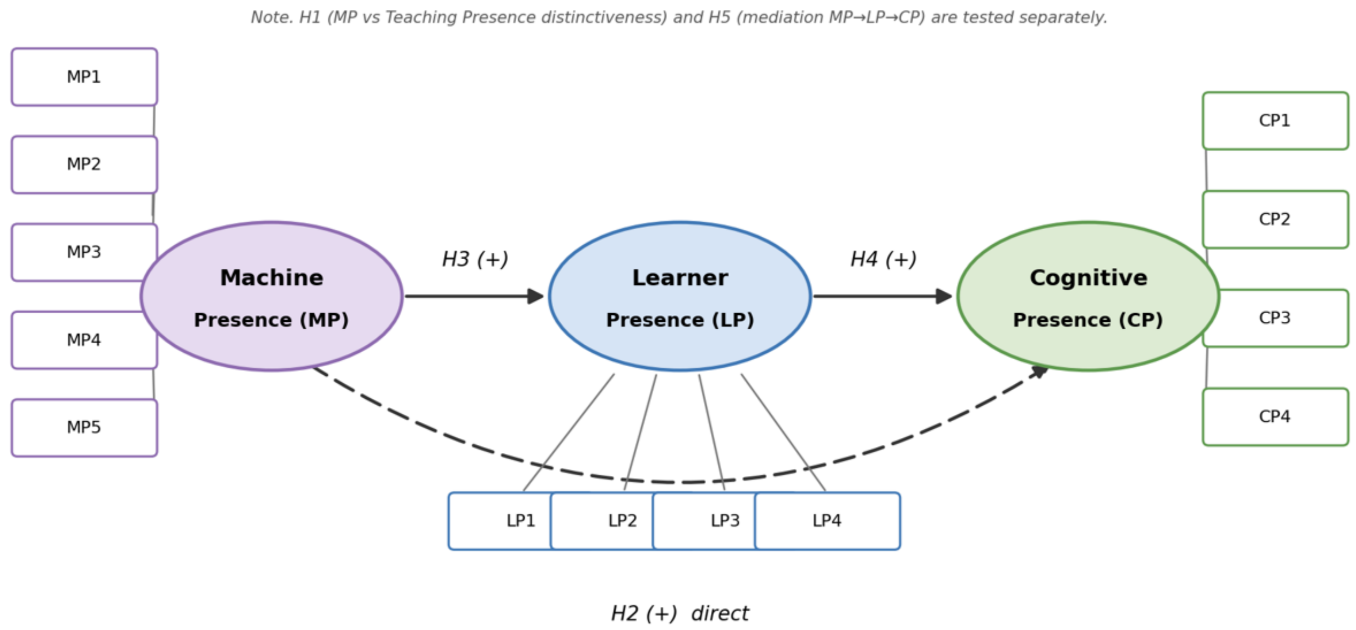

Figure 1. The hypothesized model (Machine, learner, and cognitive presence are aligned horizontally to emphasize the mediating role of learner presence; Solid arrows denote the hypothesized associations (**H2**-**H4**); The dashed path represents the direct machine → cognitive association (**H2**), which passes behind the learner presence mediator; **H1** [distinctiveness of machine vs. teaching presence] and **H5** [mediation] are tested separately) (the authors' own elaboration)

Conceptual Model and Hypotheses

The proposed model incorporates perceived machine presence as a dimension representing learners' perception of the algorithmic agency of AI, and positions learner presence as a mediator linking machine presence to cognitive presence. Because the design is cross-sectional, hypotheses are framed as associations rather than causal effects, and the distinctiveness hypothesis is framed at the level of perception and measurement rather than theoretical independence. **Figure 1** presents the hypothesized relationships.

H1 (Perceived distinctiveness). A two-factor model separating machine presence and teaching presence items provides a better empirical fit than a one-factor model combining them, and the two constructs satisfy standard discriminant-validity criteria (Fornell-Larcker; HTMT < 0.85)—indicating that learners perceive AI-mediated guidance and instructor teaching presence as non-interchangeable, without thereby establishing that they constitute two functionally independent presences.

H2. Perceived machine presence is positively associated with cognitive presence.

H3. Perceived machine presence is positively associated with learner presence.

H4. Learner presence is positively associated with cognitive presence.

H5. The association between machine presence and cognitive presence includes a significant indirect path through learner presence (framed associationally rather than causally, given the cross-sectional design).

METHOD

Design and Participants

A quantitative, cross-sectional survey design was employed. Participants were 211 undergraduate students enrolled in an AI-supported multivariable calculus course in a mathematics-education program at a public university in Indonesia. A census approach was used, inviting all students to the accessible classes. Because inferential statistics are reported, the inferential target is interpreted under a process (super-population) view—that is, inference about the data-generating process linking these constructs for students learning under this type of AI-supported design—rather than generalization to a fixed finite population. The sample exceeds the common guideline of $n \geq 200$ for structural equation modeling (Hair et al., 2019; Kline, 2016).

AI-Supported Learning Environment, Procedure, and Fidelity

Over a four-week module covering partial derivatives and double integrals, students used a generative AI tutor pre-configured with a standardized system prompt to deliver consistent Socratic guidance. The configuration was standardized across the module and emphasized four core instructional behaviors:

(1) prompting students to identify relevant mathematical variables and conditions before proceeding,

(2) providing strategic hints and procedural cues when students encountered difficulties, without completing the problem,

(3) encouraging conceptual interpretation of mathematical representations before procedural execution, and

(4) redirecting requests for final answers toward questions that elicited the student's own reasoning.

For partial-derivative problems, the tutor prompted students to identify the differentiation variable and the variables held constant. For double-integral problems, it prompted interpretation of the region specified by the integration bounds before addressing computational procedures. Students interacted with the system during independent study and structured problem-solving activities; the same configuration was applied throughout. The configuration therefore operationalized machine presence in a deliberately narrow sense: students encountered an AI system whose instructional role was constrained to Socratic, answer-withholding scaffolding.

Because the design includes no comparison condition or learning-outcome measure, the module is treated as the context in which perceptions were measured, not as an intervention whose effectiveness is evaluated, and no effectiveness claims are made. Two features of this context bound the interpretation of the construct and are revisited in the limitations. First, what participants evaluated was not "AI" in a general sense but one particular implementation of AI tutoring—an assistant deliberately constrained to withhold direct solutions and to prompt Socratically. It therefore remains an open question whether a similar construct would emerge when students interact with commercially available large language models, adaptive tutoring systems, or AI applications that provide explanations or complete solutions. Second, the fidelity of student-AI interaction (including possible attempts to elicit direct answers) was not directly verified through interaction logs; this too is acknowledged in the Limitations.

Instrument Development

A structured self-report questionnaire integrated established CoI constructs with a newly developed machine presence measure. Items for cognitive, social, and teaching presence were adapted from validated CoI instruments (Arbaugh et al., 2008; Swan et al., 2009), and learner presence items from Shea and Bidjerano (2010). All items were contextualized to AI-supported multivariable calculus and rated on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree).

The machine presence measure was developed through a staged, theory-informed procedure. The starting point was a conceptual definition of the construct as learners' perception of AI-mediated Socratic, non-answer-giving scaffolding—probing questions, strategic hints, and reflective prompts—that sustains their reasoning. This domain was derived from the instructional and scaffolding functions described in the AI-in-education and Socratic-guidance literature (Holmes et al., 2019; Kim et al., 2020; Luckin et al., 2016) and was deliberately bounded against teaching presence. In particular, functions related to course design, discourse management, and broader instructor facilitation were excluded from the machine presence domain because these are central to teaching presence within the CoI framework (Arbaugh et al., 2008; Garrison, 2007). General technology-acceptance or usability perceptions were likewise excluded because the intended construct concerned the perceived instructional function of the AI rather than students' overall evaluation of the technology. The construct specification was used as the basis for both item development and expert review.

Second, the construct domain was represented through five content facets: diagnostic feedback, non-answer scaffolding, problem decomposition, conceptual focus, and reasoning refinement. Candidate items were generated for these facets and then reviewed internally for redundancy, clarity, and alignment with the defined construct domain. The purpose of this stage was to ensure that the candidate items collectively represented the intended instructional functions while avoiding unnecessary overlap among items.

Third, the resulting items underwent face- and content-validity review by a panel of three independent experts: two senior lecturers in mathematics education and one expert in educational technology specializing in AI-supported learning. The experts were provided with the conceptual definition of machine presence, its theoretical boundaries, and the intended distinction from teaching presence before evaluating the candidate items. Using this conceptual specification, experts assessed each item for theoretical alignment with Socratic scaffolding, linguistic clarity, and distinctiveness from teaching presence. Content validity was quantified using Aiken's V (Aiken, 1985). Values for the five items ranged from 0.81 to 0.94 (M1 = 0.88, M2 = 0.81, M3 = 0.94, M4 = 0.85, M5 = 0.90), with an overall mean of 0.88, indicating satisfactory content relevance and conceptual clarity. The five items were retained for empirical evaluation because they met the predefined content-validity criterion and represented the intended domain without substantive redundancy.

We characterize this process as an initial psychometric evaluation rather than a full validation. The five items were reviewed by three experts and administered to a single sample of 211 undergraduates enrolled in one multivariable calculus course; while the psychometric indicators reported below are satisfactory, this level of evidence is best interpreted as promising preliminary evidence for a new measure rather than as established validation of a new theoretical construct. Independent-sample replication, criterion-related evidence, and tests of measurement invariance across

Table 1. Indicators, survey items, and supporting references: Learner presence (LP)

No	Indicator	Survey item	Supporting references
L1*	Self-efficacy	I am confident in solving multivariable calculus problems independently [Removed: Lowest within-construct loading in EFA].	Bandura (1997), Shea and Bidjerano (2010), Zimmerman (2000)
L2	Persistence	I keep trying to solve problems even when they are difficult.	Chang et al. (2023), Shea and Bidjerano (2010), Zimmerman (1989, 2000)
L3	Metacognitive monitoring	I monitor my understanding while working through problems.	Azevedo (2005), Chang et al. (2023), Garrison (2007), Shea and Bidjerano (2010)
L4	Strategic self-management	I manage my time and study strategies well in this course.	Chang et al. (2023), Shea and Bidjerano (2010), Zimmerman (2000)

Note. L1 removed from the final model (lowest within-construct loading in EFA, alongside S3 and C3) & Final model retains L2-L4: AVE = 0.593, CR = 0.812, Cronbach's α = 0.801

Table 2. Indicators, survey items, and supporting references: Machine presence (MP)

No	Indicator	Survey item	Supporting references
M1	Diagnostic feedback	Questions from the AI helped me identify errors in my mathematical reasoning.	Holmes et al. (2019), Hwang and Tu (2021), Kim et al. (2020), Luckin et al. (2016)
M2	Non-answer scaffolding (Socratic hinting)	When I struggled, the AI provided hints without giving direct answers, encouraging me to think independently.	Kim et al. (2020), Luckin et al. (2016), Nopas (2025), Varghese (2025), Yavich (2025)
M3	Problem decomposition	Guidance from the AI helped me break complex mathematics problems into simpler steps.	Alam and Mohanty (2024), Holmes et al. (2019), Hwang and Tu (2021), Kim et al. (2020), Mukherjee (2025),
M4	Conceptual focus	The AI helped me focus on understanding concepts rather than just obtaining final answers.	Kim et al. (2020), Smutny and Schreiberova (2020), Varghese (2025), Zawacki-Richter et al. (2019)
M5	Reasoning refinement (reflective prompting)	The AI helped me test and refine my thinking without directly providing solutions.	Azevedo (2005), Chang et al. (2023), Holmes et al. (2019), Kim et al. (2020), Nopas (2025)

Note. All five MP items retained in final model; Standardized loadings ranged from 0.66 to 0.86; AVE = 0.596, CR = 0.880, Cronbach's α = 0.880; Items M2 and M5 presuppose an answer-withholding tutor and may not transfer to AI systems that provide complete solutions (see limitations)

contexts remain necessary and are identified as priorities for future work.

Learner presence was measured using four items operationalized from Shea and Bidjerano's (2010) self-regulated learning framework, covering self-efficacy, persistence, metacognitive monitoring, and strategic self-management (Chang et al., 2023; Zimmerman, 2000). **Table 1** presents the learner presence indicators, survey items, and supporting references. One item (L1, self-efficacy) was subsequently removed during model refinement due to low within-construct loading in the exploratory factor analysis (EFA). Because self-efficacy represents one aspect of learner self-regulation relevant to the original formulation of learner presence (Shea & Bidjerano, 2010), its removal narrows the operational scope of the construct in this study to its volitional and metacognitive facets (persistence, monitoring, and strategic self-management), with less representation of self-efficacy. This narrowing is acknowledged in the limitations.

Table 2 presents the five machine presence indicators, survey items, and empirical references; all five items were retained throughout the EFA, split-half confirmatory factor analysis (CFA), and final CFA stages.

Data Analysis Strategy

Analyses proceeded from EFA to CFA, with a split-half internal replication check, following a development-then-confirmation logic (Anderson & Gerbing, 1988). Convergent validity was assessed via standardized loadings, average variance extracted (AVE) (≥ 0.50), and composite reliability (CR) (≥ 0.70). Discriminant validity was evaluated using both the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio (< 0.85) (Henseler et al., 2015). To test **H1** directly, a one-factor model in which all machine and teaching presence items loaded on a single latent variable was compared with a two-factor model in which the items loaded on their respective constructs, via the chi-square difference test and changes in CFI. As a supplementary probe of whether this distinctiveness extended beyond measurement, a test of equality of nomological relations was conducted in which machine and teaching presence were specified as simultaneous predictors of cognitive and learner presence, and the corresponding paths were constrained to equality; a chi-square difference test evaluated whether the constraint worsened fit. Associations (**H2-H5**) were then estimated structurally, with the indirect path assessed by bootstrap (5,000 resamples).

To assess the robustness of the assumed directionality, an alternative model reversing the hypothesized ordering was estimated and its fit compared with that of the hypothesized model. The potential for common-method variance was examined using Harman's single-factor test (Podsakoff et al., 2003). Model fit was judged using CFI/TLI (≥ 0.90/0.95), RMSEA (≤ 0.08), and SRMR (≤ 0.08) (Hu & Bentler, 1999). EFA was conducted in SPSS; CFA, the competing-models comparison, and the structural and mediation models were conducted in AMOS. The supplementary robustness analyses—Harman's single-factor test, the test of equality of nomological relations, and the alternative-direction model—were conducted in Python using the semopy package (Igolkina & Meshcheryakov, 2020) under maximum-likelihood estimation. HTMT ratios were computed from the inter-construct correlations.

RESULTS

Factorability and Exploratory Structure

The data were suitable for factor analysis (KMO = 0.906; Bartlett's test of sphericity χ^2 (210) = 2,429.3, $p < 0.001$). In the exploratory solution, the five machine presence items loaded cleanly on a single factor that was separate from the teaching presence items, which formed their own factor—providing initial evidence that learners distinguish AI Socratic guidance from instructor teaching presence. Cognitive presence items were the weakest; item C3 showed elevated association with items from other constructs and, together with S3 and L1 (the lowest within-construct loadings), was removed prior to confirmation. As internal split-sample evidence, a split-half CFA was conducted (half A, n = 105: CFI = 0.931, RMSEA = 0.077; half B, n = 106: CFI = 0.920, RMSEA = 0.078). Given the modest size of each half-sample for confirming a multidimensional model, this evidence is best interpreted as internal replicability of the factor structure rather than as full cross-validation in the conventional sense; genuine replication will require an independent sample and is identified as a priority for future work.

Measurement Model

The initial 21-item model showed acceptable but improvable fit (χ^2 = 329.5, df = 179, CFI = 0.935, RMSEA = 0.063). Three items were removed on the basis of converging evidence. C3 showed the lowest standardized loading on cognitive presence (λ = 0.57) and the lowest corrected item-total correlation within its construct (r = 0.51). S3 showed the lowest loading on social presence (λ = 0.64) and a corrected item-total correlation of r = 0.58, also the weakest within its construct. For both C3 and S3, standardized residual diagnostics did not reveal a dominant cross-construct association, so the deletion decision was based primarily on the relatively low within-construct loading and corrected item-total correlation. L1 showed a clearer cross-construct pattern: in addition to the lowest loading on learner presence (λ = 0.60) and a corrected item-total correlation of r = 0.57, standardized residual correlations revealed substantial shared variance with all four teaching presence items (residuals ranging from -0.40 to -0.59), suggesting that students interpreted this self-efficacy item in ways closely tied to perceptions of the human instructor. Dropping each item individually produced a modest improvement in fit; dropping all three jointly yielded a clear improvement (CFI from 0.935 to 0.960; RMSEA from 0.063 to 0.056). The refined 18-item model achieved good fit overall (**Table 3**). Retained standardized loadings ranged from 0.66 to 0.86, and all constructs met the thresholds for convergent validity and reliability (**Table 4**).

Table 3. Model fit indices before and after refinement

Index	Recommended	Initial (21 items)	Final (18 items)
χ^2	-	327.9	206.4
df	-	179	125
χ^2/df	≤ 3.00	1.83	1.65
CFI	≥ 0.950	0.936	0.960
TLI	≥ 0.950	0.924	0.951
RMSEA	≤ 0.080	0.063	0.056
SRMR	≤ 0.080	0.057	0.042

Table 4. Reliability and convergent validity (final model)

Construct	Cronbach's α	CR	AVE	√AVE
Cognitive presence	0.773	0.777	0.539	0.734
Social presence	0.826	0.828	0.617	0.785
Teaching presence	0.881	0.881	0.649	0.806
Learner presence	0.801	0.812	0.593	0.770
Machine presence	0.880	0.880	0.596	0.772

Figure 2 depicts the measurement model.

Discriminant Validity and the Perceived Distinctiveness of Machine Presence (H1)

On the Fornell-Larcker criterion, the square root of AVE exceeded the inter-construct correlations for the focal pairs; in particular, machine and teaching presence correlated only 0.48, well below the √AVE of either (0.77 and 0.81). The single exception was the cognitive-social pair: their latent correlation (r = 0.75) exceeded the √AVE of cognitive presence (0.73), so the Fornell-Larcker criterion was not fully satisfied for this pair; the HTMT ratio for the same pair (0.74), however, remained clearly below the 0.85 threshold. Read together with the removal of C3 (which had shown elevated cross-construct association), these results indicate moderate empirical overlap between cognitive and social presence in this sample. We interpret the measurement model as acceptable overall, while acknowledging that the cognitive-social distinction is empirically less sharp than the other pairwise distinctions and that cognitive

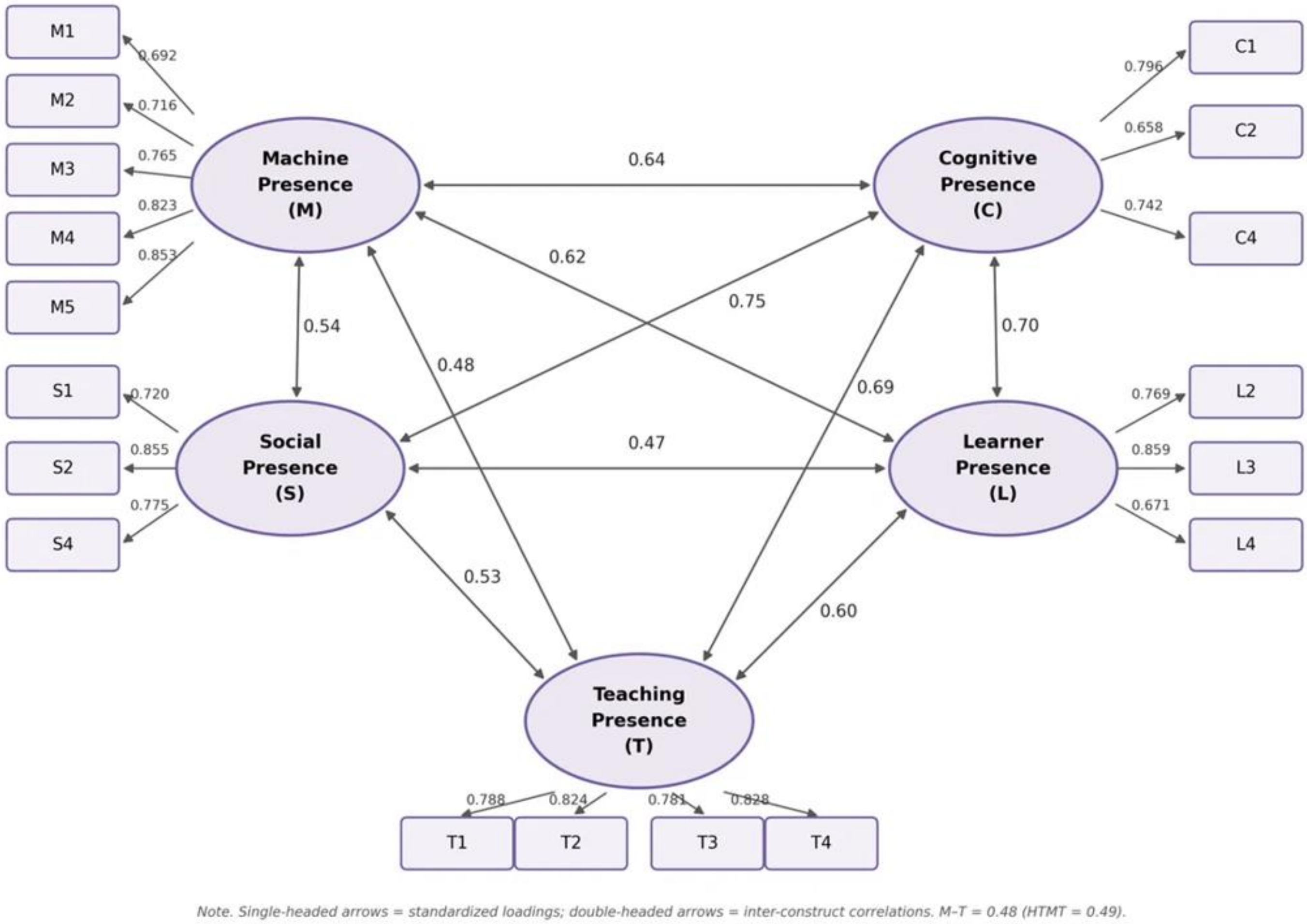

Figure 2. The measurement model (the authors' own elaboration)

Table 5. Discriminant validity: Fornell-Larcker and HTMT

	C	S	T	L	M
C	0.734	0.744	0.681	0.714	0.651
S	0.752	0.785	0.533	0.496	0.538
T	0.687	0.533	0.806	0.602	0.489
L	0.695	0.465	0.602	0.770	0.626
M	0.642	0.543	0.483	0.618	0.772

Note. C: Cognitive; S: Social; T: Teaching; L: Learner; M: Machine presence; Diagonal: √AVE; Below diagonal: Latent correlations (Fornell-Larcker); & Above diagonal: HTMT ratios

presence items may benefit from refinement in future work. HTMT ratios were all below 0.85 (maximum 0.74 for cognitive-social), and HTMT (machine, teaching) was 0.49 (**Table 5**).

The competing-models comparison favored the two-factor solution. A one-factor model combining the machine and teaching presence items fit the data poorly, whereas the two-factor model fit it far better, and the two-factor model was statistically superior ($\Delta\chi^2$ (1) = 310.9, $p < 0.001$; ΔCFI = 0.303) (**Table 6**).

Two interpretive cautions accompany this result. First, the two-factor RMSEA (0.083) marginally exceeds the 0.08 cutoff adopted here, so the two-factor solution should be read as clearly preferable to the one-factor solution rather than as an unqualified close fit for this

Table 6. Competing-models comparison (machine vs. teaching presence items)

Model	χ^2	df	CFI	RMSEA
One-factor (combined)	374.2	27	0.660	0.247
Two-factor (separate)	63.3	26	0.963	0.083

reduced item set. Second, and more importantly, a superior two-factor fit and a low HTMT establish that learners do not treat machine and teaching presence items as interchangeable indicators of a single latent variable—that is, they perceive the two as distinct. As discussed before, this evidence is consistent with both a distinct-presence interpretation and a source-attribution interpretation, and it does not by itself establish that machine presence constitutes a functionally independent educational presence. **H1**, understood as a hypothesis about *perceived* distinctiveness, was supported; the stronger claim of theoretical independence is not tested here.

To probe whether the perceived distinctness extends to a functional distinction, an additional model was estimated in which machine presence and teaching presence were entered simultaneously as predictors of both cognitive presence and learner presence. In the unconstrained model, both constructs were significantly associated with the outcomes (MP → CP: B = 0.335, p =

Table 7. Structural associations (standardized)

Path	β	CR	p
Machine → learner (**H3**)	0.617	7.350	< 0.001
Machine → cognitive, direct (**H2**)	0.341	3.632	< 0.001
Learner → cognitive (**H4**)	0.486	4.959	< 0.001

Note. Indirect association: The machine → learner → cognitive indirect path was 0.300 (total = 0.641); The bootstrap 95% CI excluded zero, indicating a significant indirect association consistent with the hypothesized mediation model; & Given cross-sectional design, this pattern is not interpreted as evidence of a causal mediating mechanism

0.001; TP → CP: B = 0.413, $p < 0.001$; MP → LP: B = 0.521, $p < 0.001$; TP → LP: B = 0.442, $p < 0.001$). When the corresponding paths were constrained to equality (MP → CP = TP → CP; MP → LP = TP → LP), model fit did not deteriorate ($\Delta\chi^2(2) = 0.539$, $p = 0.764$); that is, the constraint could not be rejected. This result should be read as a failure to detect a difference in the two constructs' nomological relations rather than as positive proof of their equivalence, since a non-significant difference is also compatible with limited statistical power at this sample size. With that caveat, the pattern is consistent with a source-attribution interpretation: learners perceive the two as distinct sources of guidance, but the perceived guidance appears to function comparably in its associations with self-regulation and cognitive engagement. The result therefore tempers any claim that machine presence functions as a presence separable from teaching presence at the level of nomological relations, while confirming that it is separable at the level of measurement and perception.

Associations Among Constructs (H2-H5)

Estimated structurally, perceived machine presence was positively associated with learner presence (β = 0.62) and with cognitive presence (β = 0.34), and learner presence with cognitive presence (β = 0.49), supporting **H2**-**H4** (**Table 7**). The indirect association of machine presence with cognitive presence through learner presence was 0.30 (total = 0.64); a bootstrap (5,000 resamples) produced a 95% confidence interval excluding zero, indicating a significant indirect association consistent with the hypothesized mediation model (**H5**). Given the equivalent fit of the reverse model (LP → MP → CP), this cross-sectional design cannot establish a causal mediating mechanism. All coefficients are interpreted as standardized associations, not causal effects; because all variables were measured concurrently with the same instrument, the direction of these associations cannot be established from the present design (see limitations).

To probe the assumption of directionality, an alternative model reversing the hypothesized ordering (LP → MP → CP) was estimated. It produced identical fit ($\chi^2 = 226.260$, df = 126, CFI = 0.951, RMSEA = 0.062), confirming that the cross-sectional design cannot adjudicate the direction of these associations; the hypothesized ordering is retained on theoretical, not empirical, grounds.

DISCUSSION

This study asked whether students perceive machine presence as distinguishable from teaching presence within the CoI framework, and how perceived machine presence is associated with self-regulated and cognitive engagement in AI-supported mathematics learning. The perceptual question received empirical support: a two-factor model separating machine and teaching presence fit the data better than a one-factor model combining them, and HTMT (machine, teaching) was well below conventional thresholds. The results thus indicate that learners in this setting perceive AI-mediated Socratic guidance as distinguishable from instructor teaching presence. Importantly, this conclusion rests on the discriminant and competing-models evidence rather than on the mere significance of structural paths, so the answer corresponds to the perceptual question actually posed.

At the same time, we take seriously the alternative interpretation that this perceptual distinctness reflects a distinction of *source* rather than of *function*. Students may recognize that guidance originates from an algorithm rather than from their instructor while nonetheless experiencing essentially the same pedagogical function—diagnostic feedback, hinting, decomposition, and conceptual focusing—that the CoI literature attributes to teaching presence. The test of equality of nomological relations reported before lends empirical weight to this reading: when the paths from machine presence and teaching presence to cognitive presence and learner presence were constrained to equality, model fit did not deteriorate ($\Delta\chi^2$ (2) = 0.539, $p = 0.764$). We are careful not to over-read this null result—failure to detect a difference is not proof of equivalence, and limited power cannot be ruled out at this sample size—but the pattern is what one would expect if learners perceive one and the same pedagogical function while attributing it to different agents. We therefore refrain from claiming that machine presence is a functionally independent dimension of the CoI framework; the present evidence is most consistent with perceptual distinctness coupled with functional similarity.

Read associationally, the structural results indicate that stronger perceived machine presence co-occurs with stronger self-regulated and cognitive engagement, and that a meaningful share of the machine-cognitive association is statistically accounted for by learner presence. This pattern is consistent with research suggesting that AI-based systems can support deeper cognitive engagement when they guide reasoning rather than supply answers (Hwang & Tu, 2021; Zawacki-Richter et al., 2019), and with the view that AI can act as an epistemic participant in knowledge construction

(Holmes et al., 2019). We deliberately refrain from describing machine presence as an "active pedagogical agent" or claiming that it "enhances" cognition, because concurrent self-report data cannot establish that the AI caused changes in learning. The direction of the observed associations is, moreover, not identifiable from these data: it is equally plausible that students who are generally more engaged, self-regulated, or positively disposed toward the course perceive the AI more favorably, so that engagement shapes perception rather than the reverse. We give this reverse-direction account, and the possibility of common-method inflation, explicit weight rather than privileging a single theoretical direction (see limitations).

The association between machine presence and learner presence is theoretically notable. It suggests that, in this environment, the perceived value of AI scaffolding is closely tied to learners' self-regulation—goal setting, monitoring, and strategic control (Chang et al., 2023; Shea & Bidjerano, 2010). This indirect-association pattern is consistent with accounts that foreground metacognitive processes as mechanisms in technology-enhanced learning (Azevedo, 2005): the relationship between system-level support and cognitive engagement appears to be co-constructed with learner-level agency rather than attributable to technology alone. Here too, the cross-sectional design means this reading is one of several compatible interpretations of the data.

Theoretically, the study makes a measured contribution. It offers a documented, preliminarily evaluated measure of perceived machine presence and an explicit test of whether learners perceive AI scaffolding as distinct from teaching presence—a perceptual discriminant test that prior extensions have lacked (Kim et al., 2020). We are careful, however, about the weight this can bear: establishing a new theoretical dimension of one of the most influential frameworks in online learning requires considerably broader evidence than a single cross-sectional study in one discipline and one institutional context can provide. What the finding does indicate is that some guidance functions may be *perceived* as distributed across human and algorithmic sources in AI-supported environments (Garrison et al., 2000; Luckin et al., 2016), an observation that itself invites further theoretical work. The marginal cognitive-social overlap observed here echoes long-standing measurement debates within CoI and points to a need for sharper cognitive presence items in mathematics contexts.

Practically, the results are consistent with designing AI tutors around prompting, hints, and reflection rather than answer delivery, especially in disciplines such as mathematics where productive struggle is integral to understanding (Selwyn, 2010; Varghese, 2025). Because learners may attempt to circumvent answer-withholding constraints, designers and instructors might also build in mechanisms that monitor and sustain inquiry-oriented use. These propositions, however, should be tested with designs capable of supporting effectiveness claims.

Limitations and Future Research

Seven limitations bound the present claims. First, the cross-sectional, single-group design—without a comparison condition, pre-/post-measures, or learning-outcome data—precludes any conclusion about instructional effectiveness or causality. Second, all constructs were self-reported and collected concurrently. As an exploratory check, a Harman single-factor test was conducted; a single unrotated factor accounted for 43.0% of the variance, below the conventional 50% threshold (Podsakoff et al., 2003). However, this test is a weak diagnostic and does not rule out common-method bias: all constructs were assessed concurrently, through the same instrument, and by the same respondents, so the possibility of common-method variance remains an active limitation of the design. In addition, the direction of association cannot be identified; an alternative structural model reversing the hypothesized ordering (LP → MP → CP) produced identical fit (χ^2 = 226.260, df = 126, CFI = 0.951, RMSEA = 0.062), confirming that a reverse or reciprocal account—in which generally more engaged, self-regulated, or positively disposed students perceive the AI more favorably—is fully compatible with these data. Third, the construct was evaluated within one specific AI implementation—a tutor deliberately constrained to withhold direct solutions and to prompt Socratically. Two of the machine presence items (M2, non-answer scaffolding; M5, reasoning refinement without solutions) presuppose this answer-withholding design, so the measure may not be invariant across commercially available large language models, adaptive tutoring systems, or AI applications that provide explanations or complete solutions; the generalizability of the construct beyond this context is therefore an open empirical question. Fourth, intervention fidelity was not directly verified; without interaction logs, the extent to which students used the AI as intended (including attempts to elicit direct answers) cannot be confirmed. Fifth, discriminant validity between cognitive and social presence was marginal on the Fornell-Larcker criterion, and the two-factor competing model's RMSEA marginally exceeded the 0.08 cutoff, indicating that some items require refinement, although the focal machine teaching distinction was robust. Sixth, and most consequentially for the theoretical claim, the study establishes perceptual and measurement-level distinctness but not functional or theoretical independence. Indeed, the test of equality of nomological relations found no detectable difference in how machine and teaching presence relate to the CoI outcomes ($\Delta\chi^2$ (2) = 0.539, p = 0.764), a result more consistent with a source-attribution than a distinct-presence interpretation, though a null difference cannot by itself confirm equivalence. Further research using experimental designs, learning-outcome measures, and different AI implementations is needed to determine whether conditions exist under which machine presence exhibits nomological relations that diverge from those of teaching presence. Seventh, the retained learner presence measure comprises persistence, metacognitive monitoring, and strategic self-management, following removal of the self-efficacy item on empirical grounds. This narrows the construct's original scope (Shea & Bidjerano, 2010) to its volitional and metacognitive facets, and results for learner presence should be interpreted accordingly; reinstating and re-testing a self-efficacy indicator is a priority for future refinements.

Future studies should employ longitudinal and experimental designs, independent-sample and criterion-related validation, and tests of measurement invariance across AI implementations and disciplines. Although the test of equality of nomological relations reported here favored a source-attribution interpretation, this result was obtained within one instructional context; whether machine presence diverges from teaching presence in its nomological relations under different AI designs (e.g., open-ended LLMs and adaptive tutoring systems) remains to be tested. Multimodal learning analytics, such as system logs and analysis of student-AI dialogue, would allow researchers to triangulate self-reports, verify fidelity, and examine the micro-processes of AI-mediated mathematical inquiry.

CONCLUSION

This study developed and preliminarily evaluated a measure of perceived machine presence and showed, through a competing-models test and HTMT, that learners perceive it as distinguishable from teaching presence within one particular implementation of AI-supported mathematics learning. Perceived machine presence was positively associated with self-regulated and cognitive engagement, and learner presence statistically accounted for part of that association. These are preliminary, associational findings—evidence that machine presence is a measurable and perceptually distinguishable perception within the CoI—rather than proof that it constitutes a fully validated, theoretically independent dimension of the framework or that the AI improved learning. More precisely, the study provides an initial operationalization of how students perceive AI-mediated instructional guidance within a specific learning environment. The test of equality of nomological relations further showed that machine and teaching presence relate to self-regulation and cognitive engagement in ways that could not be statistically distinguished, a pattern more consistent with a source-attribution interpretation—learners distinguish the agent but experience a similar pedagogical function—than with the view that machine presence is already an independent dimension. Whether conditions exist under which machine presence exhibits genuinely distinct nomological relations—and might therefore warrant the status of a theoretically independent dimension—remains an open question requiring independent-sample validation, diverse AI implementations, and designs capable of supporting causal inferences. Even so, the results suggest an evolving instructional landscape in which some functions traditionally associated with teaching presence may be perceived as distinctively algorithmic, inviting renewed attention to how human and machine guidance jointly shape inquiry.

Author contributions: FA: conceptualization, formal analysis, writing – original draft; **NH & MSR:** resources, methodology, writing – review & editing. All authors agreed with the results and conclusions.

Funding: No funding source is reported for this study.

Acknowledgments: The authors would like to thank the students of the mathematics education program at Universitas Negeri Makassar who participated in this study. The authors would also like to thank the faculty of mathematics and natural sciences at Universitas Negeri Makassar for facilitating the implementation of the AI-supported learning environment used in this research.

Ethical statement: This study was approved by the Institute for Research and Community Service at Universitas Negeri Makassar on 12 March 2026 with approval number 112/DST/UN36.12/TU/2026. The study was conducted in accordance with ethical standards for educational research involving human participants. Participation was voluntary, and informed consent was obtained from all participants prior to data collection. Participants were informed that their responses would be used solely for research purposes and would remain confidential and anonymous.

AI statement: The authors declare that generative AI tools or AI-assisted technologies were not used for manuscript writing, data analysis, interpretation of results, or generation of scientific content. The AI system described in this study was the object of investigation and was used only as part of the research context. It was not used as a tool for preparing, revising, or generating the content of this manuscript. The authors take full responsibility for the accuracy, originality, and integrity of the work presented in this article.

Declaration of interest: No conflict of interest is declared by the authors.

Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

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