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The Effects of Trust and Cognitive Load on Human-Generative AI Communication in Higher Education: Evidence from Indonesian Undergraduate Students

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Abstract
This study examines the influence of trust and cognitive load as fundamental factors associated with Human-Generative AI Communication in a higher education context. As student interactions with generative artificial intelligence systems through natural language increase, understanding the conditions that support effective and meaningful communication between humans and AI becomes crucial. Using a quantitative research design, survey data were collected from 400 Indonesian undergraduate students who had actively used a generative AI platform for academic purposes in the past three months. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to test the theoretically hypothesized influence of trust and cognitive load on Human-Generative AI Communication within a theory-driven modeling framework. Results indicate that trust has a strong and significant influence. Students who perceive AI systems as reliable and credible are more likely to engage in open, dialogic communication. Cognitive load also showed a significant influence, indicating that lower cognitive load facilitates clearer, more efficient, and more dialogic communication with AI systems. Furthermore, the combined effects of trust and cognitive load accounted for a significant portion of the variance in Human-AI Generative Communication, underscoring the role of both factors in shaping interaction quality in academic settings. The findings indicate that students' communication with generative AI is closely related to relational evaluations and perceived cognitive demands, supporting the view of generative AI as a communicative participant and not simply an instrumental tool. This study contributes to communication research by providing empirical evidence on the

socio-cognitive underpinnings of Human-Generative AI communication in higher education.

Keywords: *Generative Artificial Intelligence, Human-Machine Communication, Human-AI Communication, Trust, Cognitive Load*

1. Introduction

The rapid and widespread development of digital technologies has profoundly reshaped modern communication practices, both in theoretical conceptualization and in everyday applications. Among these innovations, generative artificial intelligence (Gen AI) is one of the most transformative developments of recent decades, fundamentally changing how communication is produced, mediated, and interpreted. Unlike previous computer systems that functioned largely as passive tools or automated processors, Gen AI platforms such as ChatGPT, Google Gemini, and Microsoft Copilot can generate natural language, simulate reasoning, and respond adaptively to user input because they are based on sophisticated large-scale language models. These capabilities enable Gen AI to engage as active conversational partners, rather than simply as technological intermediaries in human interactions.

In the higher education context, these changes have become apparent. Generative AI has gone beyond specific academic tasks, such as grammar correction and information retrieval, and has become an integral part of students' daily academic routines. Generative AI now assists in idea generation, concept clarification, argument development, and reflective dialogue (Jin et al., 2024; Nazaretsky et al., 2025). Through these dialogic interactions, Generative AI participates in the meaning-making process previously considered the sole responsibility of human speakers. As a result, the communication dynamics in academic contexts are changing. The communicative agency is increasingly shared between students and generative AI agents.

Evidence of this change is reflected in the widespread adoption of Gen AI in higher education worldwide. Empirical data indicate the extent to which this fact has been integrated. The Digital Education Council’s 2024 Global AI Student Survey, which involved 3839 students from 16 countries across undergraduate, master's, and doctoral levels, reports that 86% of students worldwide have incorporated AI into their learning processes. Complementary findings from the Chegg Global Student Survey 2025 indicate that approximately 80% of students across 15 countries actively use Gen AI for academic purposes. In this global landscape, Indonesia has the highest undergraduate adoption rate at 95%, exceeding the global average. Hence, these statistics suggest that Generative AI has become embedded not only as a supplementary learning resource but as a fundamental part of students' communication and cognitive habits. It is common for students today to resort to AI to facilitate interactions when seeking information, understanding academic texts, or generating ideas (Maral et al., 2025; Wang & Fan, 2025).

Despite the sudden, fast adoption of Gen AI in education, a significant amount of scholarly work still evaluates its impact primarily in terms of functionality, efficiency, and learning outcomes, without delving into human-AI communicative interaction. For example, a 2025 meta-analysis by Chen & Cheung (2025) confirms that studies overwhelmingly focus on the measurable outcomes, such as large effect sizes of Gen AI on students' achievement, language skills, motivation, etc. However, they say little about how students actually interact with these systems. Another research warns that this narrow view overlooks how students negotiate meaning with AI tools. As Ahmed (2025) emphasizes that communication development is fundamentally a human process. Therefore, AI integration should occur only in ways that preserve, rather than erode, the cognitive, relational, and ethical work of meaning-making. Some perspectives from different disciplines align with these concerns. The uncritical use of Gen AI can lead to 'misplaced trust' and cognitive disengagement when students, without verifying the accuracy, accept AI-generated answers as authoritative. To sum up, critical issues such as trust, interpretation, and distributed cognition in human-AI communication remain largely unaddressed in the current research, despite the high adoption rate and numerous outcome-focused studies.

One reason chatbots like Generative AI feel so natural is that they engage users in a conversational way and provide feedback tailored to the user, so the interaction is more like a conversation between two people than a one-way human-computer interaction. This is consistent with research on human-machine communication, which considers machines as communicative actors that influence the flow of interactions (Guzman & Lewis, 2020). From this perspective, communicating with Gen AI is a dialogue in which new meaning is generated through interaction rather than a simple transfer of information. This view challenges the traditional dichotomy between interpersonal and mediated communication and calls for new theoretical approaches in communication studies.

Media Equation Theory provides an important foundation for understanding this phenomenon. Reeves and Nass (1996) argued that individuals treat media and machines as social actors, particularly when those technologies display social cues, such as responsiveness, politeness, and conversational coherence. Later communication research confirms this view and further demonstrates that media systems capable of simulating social behavior elicit relational responses from users, shaping how messages are perceived, evaluated, and interpreted. (Littlejohn & Foss, 2022). In higher education contexts, these principles imply that communication with Gen AI has relational implications that extend beyond informational utility. Students may attribute credibility, intentionality, and even social presence to AI agents, thereby influencing the communicative experience itself.

Within this communicative landscape, trust is identified as one of the key factors that governs the quality of human-AI interaction. Trust determines whether students perceive AI-generated messages as credible, reliable, and worthy of engagement. Mayer et al. (1995) define trust as the willingness to rely on another party based on perceptions of ability, integrity, and benevolence. In the context of human-Generative AI interaction, trust involves users' judgments about an artificial agent's ability, consistency, and suitability for achieving their goals. Schlicker et al. (2025) expand upon this concept with the Trustworthiness Assessment Model (TrAM). TrAM distinguishes the system's actual trustworthiness from the user's perception of it. The latter is derived from observable communicative cues, such as the clarity of the message, the relevance of the answer, and the consistency of the interaction. From a communication perspective, trust in AI is not static but dynamically negotiated through interaction. Each communicative exchange contributes to users' ongoing assessment of whether an AI agent can be relied upon as a communicative partner. This process has been validated by the Computers-Are-Social-Actors (CASA) paradigm, which explains why users apply social norms and expectations to technological systems that exhibit human-like communicative behavior (Lee, 2024). Anthropomorphic design features, empathetic and communicative response, and conversational fluency can significantly increase the perception of trust, even though users are still cognitively aware that they are talking to a machine (Huynh & Aichner, 2025).

Within academic contexts, trust in generative AI is multidimensional. Nazaretsky et al. (2025) highlighted the interrelated dimensions of perceived usefulness, readiness, and trustworthiness that shape students' engagement with AI systems. Several empirical studies have shown that trust positively influences students' acceptance of AI-generated messages, their willingness to continue interacting, and their likelihood of incorporating AI feedback into their academic reasoning (Jin et al., 2024). However, trust in AI also carries potential risks. Excessive trust can lead to uncritical dependence and reduce evaluative scrutiny, while insufficient trust can foster skepticism that undermines communicative effectiveness. (Gerlich, 2025; McGrath et al., 2025). From a communicative standpoint, trust functions as a relational mechanism that shapes not only message acceptance but also the depth and quality of interaction. (Guzman & Lewis, 2020).

Alongside trust, cognitive load is a crucial cognitive-communicative factor that influences interaction with Gen AI. According to Cognitive Load Theory, human information processing is limited by the capacity of working memory, which allocates mental effort across intrinsic, extraneous, and germane load. (Sweller, 2011). In communication contexts, excessive cognitive load can hinder comprehension, disrupt meaning-making, and reduce engagement. Conversely, optimized cognitive load supports clarity, reflection, and deeper understanding. (Qu et al., 2021).

Gen AI has an ambivalent relationship with cognitive load. On the one hand, it can reduce extraneous load by organizing information, summarizing complex material, and providing structured explanations. Through cognitive offloading, users can delegate mentally demanding tasks to AI systems, freeing up cognitive resources for higher-order processing (Gerlich, 2025). However, poorly contextualized or inconsistent AI responses can increase extraneous load by forcing users to expend additional effort to verify accuracy or interpret relevance (Maral et al., 2025; Skulmowski & Xu, 2022). Thus, cognitive load functions as both a facilitator and a constraint in Gen AI communication.

In matters of great seriousness, trust and cognitive load intersect as the socio-cognitive foundations of communicative experience. A high level of trust may reduce perceived cognitive effort as users are more willing to accept AI outputs without extensive verification. Conversely, high cognitive load may prompt users to rely more heavily on AI as a simplifying agent. However, this interaction also entails potential trade-offs. Excessive trust can diminish relevant cognitive load by discouraging deep engagement, while distrust can increase cognitive load through excessive monitoring and correction. This dynamic underscores the need to examine trust and cognitive load together rather than separately.

Building on the established communication concepts and theories above, this study develops an integrative conceptual framework to explain Human-Generative AI Communication in higher education. Rather than adopting a single existing model, the framework synthesizes insights from Media Equation Theory, Human-Machine Communication, the Trustworthiness Assessment Model, and Cognitive Load Theory. Within this framework, generative AI is seen as a communicative actor whose interaction quality is determined by users’ socio-cognitive conditions. Trust is conceptualized as a relational antecedent that influences users' readiness to interact with, rely on, and interpret AI-generated messages. On the other hand, cognitive load is the mental effort required to process and evaluate AI-mediated communication. This framework proposes that trust and cognitive load function as interrelated predictors that jointly influence the quality and effectiveness of Human-Generative AI Communication. By integrating these theoretical perspectives, the framework addresses the limited availability of communication-centered models that account for both relational and cognitive factors in the use of generative AI in higher education.

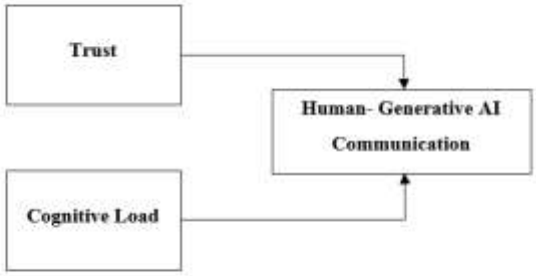

Figure 1. Conceptual Framework of Trust and Cognitive Load Effects on Human-Generative AI Communication

As illustrated in Figure 1, the conceptual framework positions trust and cognitive load as key antecedent variables influencing Human-Generative AI Communication in higher education contexts. The model assumes a causal relationship in which students’ perceptions of trust toward generative AI systems and the cognitive effort required during interaction shape the quality and effectiveness of the communication. This framework provides the theoretical basis for empirically testing the proposed relationships using a quantitative approach.

Although prior studies have begun to acknowledge the importance of trust and cognitive processes in human-AI interaction, few empirical studies have examined these constructs together as integrated socio-cognitive antecedents of human-generative AI communication. Most existing studies address trust or cognitive load in isolation, typically within technology acceptance or instructional effectiveness models. These studies rarely position trust and cognitive load within a communication-centered framework that explains how interaction quality is shaped. Furthermore, there is a dearth of quantitative investigations that explicitly test the causal influence of trust and cognitive load on human-AI communication, particularly in higher education settings. This limitation is further pronounced in the Indonesian context, where undergraduate adoption of generative AI is exceptionally high yet remains largely unexamined, and systematic, communication-focused empirical evidence remains scarce. Consequently, there is a need for a theoretically grounded, empirically tested model that explains how trust and cognitive load jointly influence human-generative AI communication.

The study addresses the following research questions: (1) How does trust influence human-generative AI communication? (2) How does cognitive load influence human-generative AI communication? (3): How do trust and cognitive load together influence human-generative AI communication? Based on these questions, the study proposes the following hypotheses: H1: Trust in artificial intelligence has a significant effect on human-generative AI communication; H2: Cognitive load has a significant effect on human-generative AI communication; H3: Trust and cognitive load together have a significant effect on human-generative AI communication.

This study contributes to the discourse on communication science by building on existing research that conceptualizes generative AI as a participant in academic interaction. By examining trust and cognitive load as key determinants of Human-Generative AI Communication, the study highlights how relational evaluations and cognitive processing demands shape interaction quality. In doing so, the research complements prior work that has primarily emphasized technical performance or learning outcomes, offering additional empirical insight into the conditions under which human-AI communication operates in higher education.

2. Methods

This study used a quantitative research design within a post-positivist paradigm to examine the causal effects of trust and cognitive load on Human-Generative AI Communication in higher education contexts. A survey-based approach was selected to assess students' perceptions and communicative experiences with generative AI systems. The study population consisted of undergraduate students enrolled at Indonesian universities who had experience using generative AI platforms for academic purposes. Given the large population of 8.281.591 based on Pangkalan Data Pendidikan Tinggi (2025), the minimum required sample was determined using Taro Yamane's (1967) formula with 5% margin of error. This sample calculation yields a target sample size of approximately 400 respondents. These respondents were acquired via a non-probability convenience sampling strategy via online academic networks and student communities. Inclusion criteria required participants to be undergraduate students who had used generative AI platforms such as ChatGPT, Gemini, or Copilot for academic activities for at least three months to ensure sustained interaction. The data collection process lasted three weeks and yielded 400 valid responses that met the inclusion criteria.

Data were collected using a closed-ended online questionnaire that measured three latent constructs: trust, cognitive load, and Human-Generative AI Communication. Trust in generative AI was conceptualized as users' belief that AI systems can produce accurate, reliable, and beneficial outputs while upholding integrity and transparency. This construct was measured through students' perceptions across three dimensions: perceived usefulness (the extent to which AI supports academic learning), readiness (students' confidence and preparedness to use generative AI), and trustworthiness (confidence in the reliability and benevolence of AI-generated responses). These indicators were adapted from Nazaretsky et al. (2025) Moreover, contextualized for use in higher education.

Cognitive load was defined as students' perceived mental effort, information-processing complexity, and cognitive resource allocation during interaction with generative AI in academic contexts. This construct was measured through students' perceptions of three types of cognitive load: intrinsic load (reflecting the complexity of information provided by AI), extraneous load (reflecting the clarity and structure of AI's information delivery), and germane load (reflecting users' effort to understand, reflect on, and integrate AI-generated responses into prior knowledge). Measurement items for cognitive load were adapted from Krieglstein et al. (2023) Moreover, tailored to generative AI platforms.

Human-Generative AI Communication was conceptually defined as the process of message exchange between human users and generative AI agents such as chatbots or virtual assistants. This construct was measured using students' perceptions of the quality of communication with generative AI in academic contexts across three dimensions. The functional dimension assessed message clarity, informational relevance, and system responsiveness; the relational dimension captured perceived social presence, politeness or empathy, and consistency of communication style; and the metaphysical dimension reflected students' perceptions of AI as a social entity or learning partner and their adaptation of communication behavior when interacting with AI. These dimensions were adapted from Guzman and Lewis (2020) and grounded in Media Equation Theory as articulated by Reeves and Nass (1996).

The questionnaire items were measured using a four-point Likert scale ranging from strongly disagree to strongly agree. This scale was intentionally selected over a five-point scale to reduce neutral-response bias and encourage respondents to express directional evaluations, which is particularly relevant when assessing emerging technologies such as generative AI. Prior to full-scale distribution, a pilot test with a small group of undergraduate students was conducted to assess item readability and preliminary reliability.

Data analysis consisted of descriptive statistics and Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS. Descriptive analysis was used to summarize respondent characteristics and general perceptions. At the same time, PLS-SEM was employed to assess the measurement model (outer loading factors, composite reliability, and average variance extracted) and the structural model (path coefficients and hypothesis testing). PLS-SEM was selected over covariance-based SEM due to its suitability for predictive modeling, robustness to non-normal data distributions, and effectiveness in analyzing complex models involving latent variables. This analytical approach aligns with the study's objective of explaining how trust and cognitive load predict Human-Generative AI Communication rather than confirming a well-established theory. To clarify the research process, a detailed research flowchart is presented in Figure 2 below, outlining the steps.

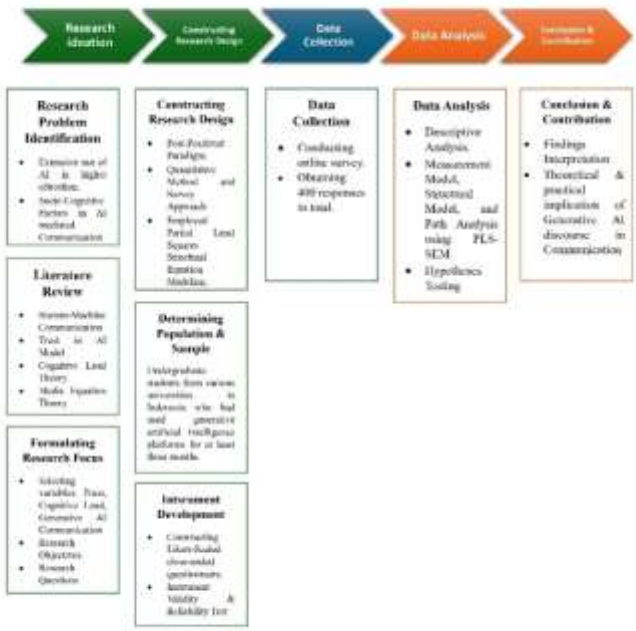

Figure 2. Research Flow Diagram

3. Results

This study analyzed data from 400 undergraduate students enrolled at various universities across Indonesia who had used generative AI platforms, including ChatGPT, Copilot, and Google Gemini, for academic purposes in the preceding three months. The sample size was determined using the Taro Yamane formula with a margin of error of **e = 0.05**, based on a total population of 8.281.591 undergraduate students (Pangkalan Data Pendidikan Tinggi, 2025). The respondents were predominantly aged 18-23 years, a demographic widely recognized as the most active cohort in adopting generative AI within educational settings. This age profile suggests that the findings reflect communicative practices among students who are highly familiar with AI integration in their learning environments.

Participants represented diverse academic disciplines, including Science and Technology (22.8%), Economics and Business (21.5%), Social Sciences and Humanities (20%), Education (18.8%), and Health Sciences (17%). This disciplinary spread indicates that engagement with generative AI is not limited to specific fields and reinforces the relevance of human-generative AI communication across academic domains.

Regarding experience, 38% of respondents reported using AI for 6-12 months, 33.33% for 3-6 months, and 28.7% for more than 1 year, with ChatGPT as the most frequently used platform. Most students reported using generative AI one to three times per week, primarily to support coursework completion, studying, and idea development, suggesting that the interaction between humans and AI has become an integral component of students' academic communication practices.

Descriptive analysis conducted prior to further analysis revealed consistently positive perceptions across all examined constructs. Importantly, these descriptive patterns do not emerge in isolation but reveal an interconnected configuration among trust, cognitive load, and Human-Generative AI Communication, suggesting that relational evaluation and cognitive manageability co-occur with students' perceptions of communicative quality.

The trust variable achieved an overall score of 75.58%, reflecting favorable evaluations across its dimensions: perceived usefulness (75.26%), readiness (75.51%), and trustworthiness (75.95%). These results suggest that students not only recognize the instrumental value of generative AI but also feel sufficiently confident and prepared to rely on it as part of their communication dynamics in educational contexts. Comparable levels of trust have been reported in prior studies on human-AI interaction in educational settings (Chan & Hu, 2023; Daher & Hussein, 2024), indicating that trust functions as a recurring relational condition rather than a context-specific anomaly.

Cognitive load exhibited a similarly high overall score of 75.80%, with intrinsic load (76.08%), extraneous load (75.71%), and germane load (75.61%) also showing similarly high scores. These results imply that students generally perceive their interaction with AI as cognitively manageable. Rather than experiencing overload, students appear to view generative AI as supporting comprehension and reducing unnecessary mental effort. This pattern is consistent with research demonstrating that AI-supported learning environments can reduce extraneous cognitive load through structured output and summarization (Koltovskaia et al., 2024).

Human-Generative AI Communication yielded an overall score of 76.55%, comprising functional (76.59%), relational (75.31%), and a notably high metaphysical dimension (93.69%). The notably high score on the metaphysical dimension can be explained by the nature of the indicators used to measure this construct. The items reflect students' perceptions of generative AI as more than a functional tool, emphasizing its role as a conversational partner that stimulates thinking, shapes communicative behavior, and influences how interaction is conceptualized. Specifically, students reported viewing AI as a partner capable of stimulating their thinking, adjusting their communication style to be better understood by AI, and experiencing interactions with AI as resembling human communication. Other items capture students' awareness that interaction with AI affects how they express ideas and alters their broader understanding of human and AI interaction. Collectively, these responses indicate that students engage in reflective and adaptive communication when interacting with generative AI, recognizing its influence on both their communicative practices and cognitive processes. Rather than indicating measurement inflation, the elevated metaphysical score reflects the extent to which students cognitively and communicatively integrate generative AI into their academic discourse, aligning with perspectives from human-machine communication that emphasize the attribution of social and communicative agency to advanced AI systems. Such perceptions provide important context for interpreting the subsequent structural relationships.

Compared with prior studies that conceptualize AI interaction primarily as instrumental or task-oriented, this finding suggests a shift toward socially and cognitively embedded communication, particularly among digitally fluent undergraduate populations. Collectively, these responses indicate that students engage in reflective and adaptive communication when interacting with generative AI, recognizing its influence on both their communicative practices and cognitive processes.

Taken together, the descriptive findings reveal a systematic relationship among the three core categories examined in this study. Trust reflects students' relational evaluation of a generative, credible, and dependable interlocutor, cognitive load captures the perceived mental effort involved in sustaining interaction, and Human-Generative AI Communication represents the perceived quality of message exchange across functional, relational, and metaphysical dimensions. This thematic alignment provides an initial empirical basis for examining how relational and cognitive conditions jointly relate to communicative engagement with generative AI in academic contexts.

To facilitate cross-construct comparison, Table 1 below summarizes the descriptive findings across constructs and their respective dimensions. This comparative presentation clarifies how students evaluate relational, cognitive, and communicative aspects of interaction with generative AI and provides context for interpreting the structural relationships.

Table 1. Summary of Descriptive Findings by Construct and Dimension

Construct	Dimension	Mean Percentage (%)	Interpretive Focus
Trust	Usefulness	75.26	Instrumental evaluation of AI support
	Readiness	75.51	Confidence and preparedness to use AI
	Trustworthiness	75.95	Perceived reliability and credibility
Cognitive Load	Intrinsic Load	76.08	Perceived complexity of AI-provided information
	Extraneous Load	75.71	Clarity and presentation of AI output
	Germane Load	75.61	Cognitive effort to integrate AI responses

Construct	Dimension	Mean Percentage (%)	Interpretive Focus
Human-Generative AI Communication	Functional	76.59	Message clarity and relevance
	Relational	75.31	Social presence and interactional tone
	Metaphysical	93.69	Perception of AI as a communicative partner

As shown in Table 1, trust and cognitive load exhibit relatively balanced scores across their respective dimensions, indicating stable relational evaluations and cognitively manageable interactions with generative AI. In contrast, the metaphysical dimension of Human-Generative AI Communication is substantially higher than its functional and relational dimensions. This pattern reflects how students conceptualize generative AI not merely as an instrumental tool, but as a communicative partner that shapes thinking, influences communicative behavior, and affects how interaction itself is understood. Rather than indicating measurement inflation, the elevated metaphysical score captures students' reflective and adaptive engagement with AI as a socially and cognitively salient presence, providing important context for interpreting the subsequent structural relationships.

To confirm that these descriptive trends were supported by robust measurement properties, the study next assessed the outer model through validity and reliability testing. The outer model evaluation ensured that all measurement items for each construct were both valid and reliable before proceeding to the structural model analysis. Hair et al. (2021) stated that the assessment covered convergent validity, discriminant validity, and internal consistency reliability. Convergent validity was assessed using outer loadings and Average Variance Extracted (AVE).

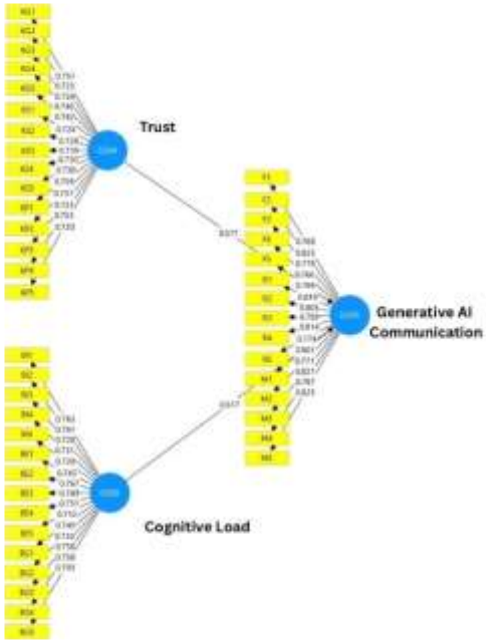

Figure 3. Outer Loading Factors

As illustrated in Figure 3, all indicators showed outer loadings above 0.70, meeting the required threshold and confirming that each item effectively represented its respective construct.

Table 2. Average Variance Extracted Value for Each Construct

Variables	*Average Variance Extracted (AVE)*	Critical Value	Information
Trust	0.544	**>0.50**	Valid
Cognitive Load	0.550		Valid
Human-Generative AI Communication	0.635		Valid

Table 2 above shows that all constructs exceed the recommended minimum of 0.50, indicating that each construct explains over half of the variance in its indicators. The result confirms that each item consistently measures its intended dimension.

Table 3. Discriminant Validity Value (HTMT)

	Original Sample (O)	Sample Mean (M)	2.5%	97.5%
Trust ↔ Cognitive Load	0.072	0.105	0.076	0.164

	Original Sample (O)	Sample Mean (M)	2.5%	97.5%
Cognitive Load ↔ Human-Generative AI Communication	0.633	0.633	0.561	0.697
Trust ↔ Human-Generative AI Communication	0.574	0.574	0.505	0.638

The discriminant validity test ensured that each construct was empirically distinct and non-overlapping. Using the Heterotrait-Monotrait Ratio (HTMT) developed by Henseler, Ringle, and Sarstedt (2015) and recommended by Hair et al. (2022)All constructs displayed HTMT values below the 0.85 threshold, confirming satisfactory discriminant validity. The bootstrap confidence intervals (2.5% and 97.5%) excluded 1.0, indicating that trust, cognitive load, and generative AI communication represent distinct theoretical dimensions.

Table 4. Reliability Test

Variables	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Information
Trust	0.940	0.940	0.947	Reliable
Cognitive Load	0.942	0.942	0.948	Reliable
Human-Generative AI Communication	0.959	0.960	0.963	Reliable

The reliability test results in Table 4 indicate that all constructs in this study met the established criteria by exceeding the minimum threshold of 0.70, confirming that each construct demonstrated strong internal consistency and that all items reliably represented the same latent variable.

Table 5. Model Fit

Model	Original sample (O)	Sample Mean (M)	95%	99%
Saturated model	0.055	0.035	0.038	0.040
Estimated model	0.055	0.035	0.038	0.040

The model fit test assessed the extent to which the structural model fit the empirical data. Using the Standardized Root Mean Residual (SRMR) index recommended by Hair et al. (2021)Both the saturated and estimated models produced an SRMR of 0.055, which is below the 0.08 threshold. This indicates a good model fit and confirms that the structural model accurately represents the theoretical relationships among the study's constructs.

Table 6. Multicollinearity Assessment (VIF)

Structural Path	VIF
Trust → Human-Generative AI Communication	1.003
Cognitive Load → Human-Generative AI Communication	1.0003

Multicollinearity was assessed using the Variance Inflation Factor (VIF) to ensure that the independent variables do not exhibit excessive correlation that could bias the structural model estimates. As shown in Table 6 above, both trust in artificial intelligence and cognitive load have VIF values of 1.003. These values are substantially below the recommended threshold of VIF < 5, as suggested by Hair et al. (2021), indicating that multicollinearity is not a concern in this model.

Table 7. R-square Values

Dependent Variable	R^2	R^2 adjusted
Human-Generative AI Communication	0.631	0.629

The inner-model evaluation assessed the explanatory and predictive power of the relationship among trust, cognitive load, and generative AI communication. As shown in Table 7, the R^2 value of 0.631 indicates that the two predictors together explain 63.1% of the variance. According to Hair et al. (2019)This level of R^2 value represents substantial explanatory power, suggesting that the model effectively captures students' communicative engagement with Generative AI in higher education contexts. This finding highlights the centrality of relational and cognitive conditions in AI-mediated academic interaction. The remaining unexplained variance suggests that additional factors, such as individual differences in AI literacy, disciplinary communication norms, or ethical orientations, may further shape how students interact and communicate with generative AI, offering directions for future research.

Table 8. Effect Size

	f^2	**Information**
Trust Level → Human-Generative AI Communication	0.899	Large
Cognitive Load → Human-Generative AI Communication	0.722	Large

An effect size (f^2) analysis was then performed to determine the contribution of each independent variable to the dependent variable. Table 8 shows the F2 values for both paths. According to Cohen's (1988) criteria, as cited in Hair et al. (2019)An effect size of 0.02 is considered small, 0.15 medium, and 0.35 or higher large. Thus, the f^2 values obtained in this study exceed 0.35, indicating a large effect size on generative AI communication. These results indicated that including these constructs meaningfully enhances the model's explanatory power.

These results also provide deeper insight into the practical relevance of the structural relationships. Both trust and cognitive load exhibit large effect sizes, indicating that their influence extends beyond statistical significance. The strong effect of trust underscores the importance of students' confidence in AI reliability and credibility for sustaining meaningful communication. When students trust AI systems, they are more willing to engage in dialogue, accept feedback, and integrate AI-generated responses into their academic reasoning. Similarly, the large effect of cognitive load suggests that communication quality improves when AI systems support efficient information processing and reduce unnecessary mental strain. Beyond descriptive convergence, the structural analysis clarifies how trust and cognitive load are statistically associated with Human-Generative AI Communication within the tested model.

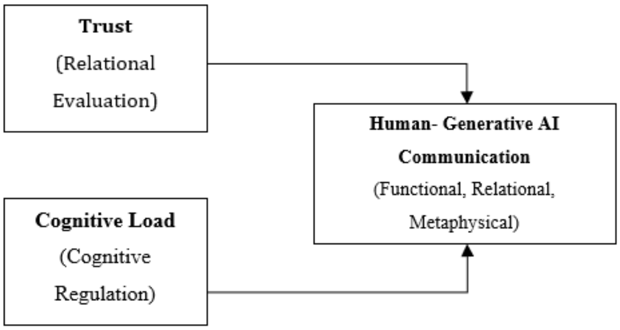

Figure 4. Relationship Flow of Human-Generative AI Communication

Figure 4 above synthesizes the empirical findings by illustrating the structural relationships among the study variables. Trust represents students' relational evaluation of generative AI, while cognitive load reflects the degree of cognitive regulation experienced during interaction. Both variables are empirically associated with perceived quality of Human-Generative AI communication. Importantly, the figure does not imply temporal precedence or causal direction; rather, it visualizes the structural associations tested in the PLS-SEM model.

Table 9. Predictive Relevance (PLSpredict)

Endogenous Variable	Q^2predict	RMSE	MAE
Human-Generative AI Communication	0.624	0.616	0.499

To further evaluate the model's predictive performance, a Predictive Relevance test was conducted using the PLS Predict procedure. The analysis produced a Q^2predict greater than 0, indicating that the model possesses strong predictive relevance. Additionally, the predictive error metrics demonstrated acceptable predictive accuracy, as indicated by RMSE and MAE values. According to Hair et al. (2022)Positive Q^2predict values, combined with low RMSE and MAE values, confirm that the structural model can generate predictions that closely approximate the observed data. Thus, the model effectively explains variance and predicts outcomes related to AI communication behaviors. This strengthens the empirical credibility of the proposed relationships.

The following step is hypothesis testing. Hypothesis testing in this study was conducted using SmartPLS and bootstrapping to assess the validity of previously formulated hypotheses. A total of 5,000 bootstrap subsamples were generated to estimate standard errors and bias-corrected confidence intervals.

Table 10. Hypothesis Test Results

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T statistics (|O/STDEV|)	P Values	Note
Trust Level → Human-Generative AI Communication	0.577	0.577	0.029	19.832	0.000	Accepted (Significant)
Cognitive Load → Human-Generative AI Communication	0.517	0.518	0.030	17.108	0.000	Accepted (Significant)

Table 10 presents the results of the structural path analysis used to test the proposed hypotheses. Hypothesis testing was conducted using the bootstrapping procedure in SmartPLS with 5,000 subsamples to estimate path coefficients, standard errors, and statistical significance. As the focus of this study is on hypothesis testing rather than interval estimation, confidence intervals are reported via bootstrap-based significance testing, consistent with common PLS-SEM reporting practices. The interpretation of results focuses on statistically supported structural relationships within a theory-driven model rather than claims of temporal causation.

The results indicate that H1 is supported: trust in artificial intelligence has a positive, statistically significant effect on human-generative AI communication ($\beta = 0.577$, $t = 19.832$, $p < 0.001$). This finding suggests that higher levels of trust enhance the quality and continuity of students' communicative interaction with generative AI systems. Similarly, the results provide support for H2, showing that cognitive load has a significant positive effect on human-generative AI communication ($\beta = 0.517$, $t = 17.108$, $p < 0.001$). This indicates that when interaction with generative AI is perceived as cognitively manageable, students are more likely to engage in clearer, more effective communication with AI systems. In addition, the joint influence of trust and cognitive load, as proposed in H3, is reflected in the structural model's substantial explanatory power. Together, these variables explain 63.1% of the variance in human-generative AI communication ($R^2 = 0.631$), demonstrating that trust and cognitive load function as complementary socio-cognitive conditions shaping students' communicative engagement with generative AI in higher education contexts.

All things considered, tested structural relationships operationalize the proposed socio-cognitive model by specifying theory-driven directional paths from trust and cognitive load to Human-Generative AI Communication. While these relationships do not establish temporal causality, they clarify how relational evaluation and cognitive manageability are statistically associated with students' perceived communicative engagement with generative AI within the modeled framework. This structural summary provides a conceptual bridge between the descriptive results and the interpretive discussion that follows.

4. Discussion

The findings of this study provide empirical support for the hypothesis that trust and cognitive load influence Human-Generative AI Communication in higher education, rather than treating these variables as peripheral conditions. Importantly, these findings align with and extend previous research by demonstrating that relational and cognitive conditions operate simultaneously within a single communicative framework. PLS-SEM results indicate that both constructs exert statistically significant influence and together explain 63.1% of the variance in students' perceptions of Human-Generative AI Communication. Within a post-positivist, theory-driven modeling framework, these effects are interpreted as model-based directional relationships specified by prior theory, rather than as evidence of temporal precedence, given the cross-sectional design. This level of explanatory power suggests that communication with generative AI is systematically structured by and linked to socio-cognitive conditions, in which relational appraisals and the regulation of mental effort jointly shape how interactions are perceived and sustained.

The strong and significant effect of trust on human-generative AI communication suggests that students' engagement with AI is influenced more by relational evaluation than purely instrumental considerations. Students who perceive AI systems as reliable and consistent tend to interact with them more openly and dialogically, treating AI-generated messages as communicative contributions rather than tentative technical outputs. This pattern aligns with Media Equation Theory (Reeves & Nass, 1996), which explains why users respond to machines as if they were social actors. It is also consistent with empirical evidence from previous studies showing that trust fosters sustained engagement and interactional continuity (Chan & Hu, 2023; Daher & Hussein, 2024). These findings also align with Schlicker et al's (2025) assertion that perceived competence, reliability, and integrity constitute the foundation of trust in human-AI interaction. The findings of this study do not indicate that trust necessarily enhances communication quality. Rather, they indicate that trust plays a significant role in shaping how communication with AI is understood and enacted. In other words, trust does not ensure positive communication outcomes. Unlike research that primarily frames trust in terms of system accuracy or task performance, the present study highlights trust as a communicative evaluation through which AI-generated messages are interpreted as meaningful contributions rather than provisional technical outputs. This emphasis aligns with human-machine communication perspectives that conceptualize advanced AI systems as socially evaluated interlocutors rather than neutral information tools (Guzman & Lewis, 2020).

In addition to confirming a positive association between trust and Human-Generative AI Communication, the findings also invite critical reflection on how trust may operate ambivalently within academic interaction. The magnitude of the trust effect warrants critical consideration. While trust is associated with reduced uncertainty and greater communicative openness, high levels of reported trust may also reflect a tendency toward uncritical acceptance of AI outputs. From a communication perspective, trust operates not only as an enabler of interaction but also as a factor that may redistribute interpretive responsibility within academic discourse. This interpretation is offered as a theoretical implication rather than a demonstrated behavioral outcome. Given the self-reported, cross-sectional nature of the data, elevated trust levels may partly reflect social desirability bias or normative expectations regarding AI use in academic settings rather than stable relational orientations toward AI systems. Thus, while the findings support a significant association between trust and Human-Generative AI Communication, they do not permit strong claims about epistemic dependence or diminished critical engagement over time.

The significant influence of cognitive load on generative AI communication, supported by a large effect size ($f^2 = 0.722$), indicates that communicative quality is constrained by users' cognitive processing capacity. This pattern is consistent with prior research demonstrating that AI-supported learning environments can reduce extraneous cognitive burden and facilitate clearer message comprehension (Jiang et al., 2024; Koltovskaia et al., 2024). However, unlike experimental studies that directly measure learning performance or task outcomes, the present findings reflect students' subjective communicative experiences, suggesting that cognitive load primarily conditions how interactional fluency and clarity are perceived rather than guaranteeing deeper cognitive engagement.

Consistent with Cognitive Load Theory, the findings suggest that students perceive interaction with generative AI as more communicatively smooth when AI systems reduce extraneous cognitive effort through organization, summarization, and clearer presentation. This interpretation is also aligned with Koltovskaia et al's (2024), who demonstrate that AI-supported learning environments can lower perceived cognitive burden and enhance message comprehension. Nevertheless, the interpretation of a "communicative paradox" associated with reduced cognitive load must be approached with restraint. While reduced cognitive effort is associated with more manageable interaction, the present study does not directly measure depth of cognitive engagement or reflective processing. Therefore, the suggestion that reduced cognitive effort may suppress germane cognitive work remains an interpretive inference rather than an empirically demonstrated outcome. Alternative explanations, such as students' prior familiarity with AI tools or task-specific efficiency gains, may also account for these perceptions. As such, cognitive efficiency should not be uncritically equated with either communicative richness or cognitive impoverishment, particularly in the absence of longitudinal or experimental evidence.

When compared with prior experimental and task-performance-oriented studies, the present findings reveal both convergence and divergence in how generative AI influences academic interaction. Consistent with previous research, reduced cognitive load is associated with clearer and more manageable interactions, and trust supports sustained engagement (Chan & Hu, 2023; Jiang et al., 2024; Koltovskaia et al., 2024). However, unlike experimental studies that operationalize outcomes as learning performance or task accuracy, this study captures students' subjective communicative experiences. This difference can be attributed to the study's communicative focus and cross-sectional, self-reported design, which foregrounds perceived interactional fluency and meaning-making rather than objective task outcomes. In contexts where no direct performance differences are observed, these findings suggest that generative AI primarily shapes how communication is experienced by reducing perceived mental effort and increasing relational confidence, rather than directly determining cognitive depth. This contributes to human-generative AI communication research by empirically demonstrating how trust and cognitive load jointly configure communicative quality in higher education, with practical implications for designing AI systems that support clarity and efficiency while encouraging reflective and responsible academic engagement.

Building on the comparative and interpretive logic above, the most consequential insight of this study emerges from the concurrent effects of trust and cognitive load. When students report high relational confidence in AI systems alongside reduced cognitive effort, their communication with generative AI is perceived as more fluent, sustained, and conversational. This pattern helps explain why Human-Generative AI Communication may shift from functional information exchange toward more socially resonant interactional forms. Within those points of view, this finding aligns with Glikson & Woolley (2020) who stated that trust functions as a core condition for communicative cooperation, while Jiang et al. (2024)' s work demonstrates that AI systems enhance cognitive efficiency by easing mental workload and improving message comprehension. These results do not imply that communicative dependence is inevitable; rather, they point to conditions under which communicative agency may be negotiated and redistributed between human users and AI systems.

The findings of this study highlighted the dynamic ambivalence in Human-Generative AI communication. Generative AI enables accessible, efficient, and responsive communication while simultaneously reshaping how authority, responsibility, and interpretive labor are negotiated in academic contexts. This is what distinguishes Human-Generative AI Communication from earlier forms of computer-mediated communication, in which relational agency was more clearly human-centered. In other words, these present findings underscore the importance of examining not only whether AI supports effective communication but also how such effectiveness may subtly reconfigure communicative norms and expectations in higher education. Practically, these findings suggest that the design and implementation of generative AI in higher education should prioritize calibrated trust and cognitive support mechanisms, such as transparency cues, dialogic prompts that encourage user reflection, and interaction designs that reduce unnecessary cognitive burden without positioning AI systems as unquestioned epistemic authorities.

The present study does not claim conceptual novelty. Instead, it contributes to the field by empirically placing trust and cognitive load within a single theory-driven model of human-generative AI communication. While socio-cognitive perspectives have been employed in prior human-machine communication studies, this research demonstrates how relational factors, such as trust, and cognitive factors collectively affect perceived communication quality amid the massive adoption of generative AI. By highlighting this interplay, the study broadens the scope of existing outcome-centered research, offering a more nuanced comprehension of human-generative AI communication as a socially situated, cognitively conditioned process open to critical inquiry within the communication science discourse.

5. Conclusion

This study concludes that among Indonesian undergraduate students, Human-Generative AI Communication is significantly associated with students' levels of trust in artificial intelligence and their perceived cognitive load during interaction. The findings of this study indicate that in this specific educational and cultural setting, relational evaluations of AI credibility and perceptions of mental effort are closely linked to how students engage in communicative interactions with generative AI systems. These results support existing Human-Machine Communication research by empirically confirming that communication with generative AI is not solely shaped by functional performance but is also systematically related to socio-cognitive factors that influence message acceptance, interactional openness, and perceived communicative quality.

Several limitations warrant careful consideration. First, reliance on self-reported survey data introduces the possibility of common-method bias and social desirability effects, particularly given the widespread adoption of generative AI tools such as ChatGPT, which dominated platform use in this sample. Second, although the measurement model met established validity and reliability criteria, potential conceptual overlap between trust-related perceptions and reduced cognitive effort cannot be entirely ruled out and warrants closer examination in future studies. Third, the cross-sectional design limits insight into how trust calibration and cognitive engagement evolve over time, and the focus on Indonesian undergraduates constrains generalizability across cultural, institutional, and technological contexts. Building on these limitations, future research should pursue longitudinal designs to examine how repeated interactions reshape trust and cognitive reliance; comparative studies across cultural or disciplinary contexts to assess contextual variability; and qualitative or discourse-analytic approaches to explore how students negotiate authority, responsibility, and meaning in human-AI communication. For communication practitioners and system designers, the findings suggest the need for intentional trust calibration and cognitive support mechanisms, such as transparency cues, prompts that encourage user reflection, and interaction designs that reduce unnecessary cognitive burden without positioning AI systems as epistemic authorities. In this way, the study provides modest, context-specific, yet meaningful empirical insight into the conditions under which Human-Generative AI

Communication operates in higher education, complementing rather than replacing existing theoretical frameworks in communication science.

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