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Human–GenAI Interaction in Higher Education: Trust as a Central Mechanism Shaping Learning Enhancement and Trade-offs

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Article

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Abstract

While generative artificial intelligence (GenAI) is ubiquitous in higher education, there is only sparse empirical evidence to inform us of the learning impact of human–GenAI interaction. This study aims to fill this void, exploring how students' engagement with GenAI can impact their learning outcomes by studying trust as a mediating variable and taking into account task-oriented learning trade-offs.

The proposed framework was validated using survey data from higher education students, and applying structural equation modeling. The findings indicate that the interaction with GenAI in collaboration with the findings of trust is the primary driver in learning outcomes. The positive effect of trust on learning enhancement was complemented by the increase in perceived learning trade-offs, revealing the dual nature of trust in AI-mediated learning.

Mediation analysis results show that the relationship between interaction and learning outcomes is partially mediated by trust. The results of the effect sizes show that the interaction effect and the task-oriented use are relatively weak factors in the model, while the trust effect is relatively high. Multigroup analysis shows that Academic level and Gender are key factors in the structural differences, while Usage level is not. This implies that quality of interactions and the formation of trust is more important than the level of usage.

The research further contributes to the development of the interaction-centered approach to GenAI in higher education and presents empirical evidence for creating meaningful human–AI interactions with good learning outcomes while avoiding potential adverse effects.

Introduction

Generative artificial intelligence (GenAI) has quickly revolutionized the world of higher education, changing the way in which students interact with the learning experience, academic activities, and knowledge construction. As increasingly more AI-powered tools become available, students can now create content, obtain real-time feedback, and engage in systems that simulate human-like responses. Such advances have profoundly transformed traditional learning spaces, leading to new possibilities for personalized, flexible, and scalable learning (Xiaoyu et al., 2025). Moreover, GenAI has led to significant questions about its impact on learning quality, engagement, and academic outcomes.

The research on GenAI in higher education that has been conducted to date has focused mostly on the functional aspects of the technology, such as its ability to assist academic writing, improve productivity, and enhance learning efficiency (Gabay et al., 2026). Although these studies have many valuable insights into what GenAI can do, they do not provide much insight into how students interact with these systems in the learning process. This is one of the critical gaps because the availability of tools is not the only factor used to define learning outcomes but rather the nature and quality of the interaction between learners and AI systems.

However, the recent debate has started to turn to the analysis of human-AI interactions as a key aspect of AI-mediated learning. According to this point of view, one of the most efficient ways to learn is the way in which students interact with AI, perceive its products and incorporate it into their academic routine. Nonetheless, even with this new area of interest, there is a paucity of empirical data that elucidates what makes effective interaction, why some interactions yield superior gains, and how this operates to affect positive learning outcomes as well as possible trade-offs.

One of the most important mechanisms that can explain such relationships is trust in generative AI. The main consideration of the trustworthiness and utility of AI-generated outputs should be the central aspect of the willingness to trust and use AI systems as students engage with AI systems. Previous studies indicate that trust has a moderating effect on engagement and learning outcomes, but its mediating effect on AI-supported learning is under researched. Moreover, the existing research tends to ignore the variation in these relationships among diverse student populations, including their academic level and gender, to narrow the scope of comprehension of heterogeneity in learning mediated by AI.

To fill these gaps, the current paper investigates how human–GenAI interaction influences learning outcomes in higher education in terms of trust and considers the impact of task-oriented use and the existence of trade-offs in AI-mediated learning. In addition, the research implements a multigroup analytical method to examine the discrepancy among groups of students to obtain more detailed insight into the impact of GenAI on learning in different settings.

This research contributes to the expanding literature on generative AI in higher education through an integrated approach to incorporating interaction processes, mechanisms of trust, and learning outcomes into one framework. In particular, it addresses recent demands to conduct research beyond tool-centric views on the mechanisms that mediate how interaction with GenAI can influence educational outcomes. The results can be used both with theory and in practice to create effective and responsible AI-enabled learning environments.

Theoretical Background

Generative AI and interaction-centered learning in higher education

Generative artificial intelligence (GenAI) has rapidly gained traction in higher education, offering innovative support services, content creation, and learning experiences. The current literature indicates its capacity to increase student efficiency and the quality of student work, especially in the areas of writing, summarizing and clarifying concepts. For example, GenAI technologies have been found to assist students in structuring arguments and refining language skills in real time to increase the efficiency and quality of work (Gabay et al., 2026). Likewise, adaptive feedback AI systems facilitate the understanding of difficult concepts and support the learning process (Xiaoyu et al., 2025).

Beyond its practical affordances, GenAI is being embedded in learning environments in a manner that has a transformative effect on the learning experience. GenAI is not only a tool to be used passively but rather through interaction based on dialog and iteration. This enables students to explore information, explore feedback and refine their learning through iterative processes. This interaction-based learning indicates a transition in learning processes, where learners are no longer passive consumers of information but active knowledge builders through ongoing interactions with GenAI.

This shift from tool-centered to interaction-centered viewpoints marks a critical shift in the literature. Previous studies have mainly assessed GenAI in terms of its performance and quality. However, recent research highlights that learning results depend not on the features of the tools but on interactions with AI systems. Here, processes such as task-oriented use, feedback-driven processes and interaction quality have been recognized as keys to AI-mediated learning. Task-oriented use is helpful for academic tasks such as writing and problem solving, whereas feedback-driven learning allows learners to improve their work iteratively and self-regulate learning (Mirzaei & Khayer, 2025). Additionally, interaction quality (depth, adaptiveness, and engagement) is important in shaping the amount of learning that is superficial or becomes cognitively meaningful (Roy, 2026).

While the use of GenAI offers benefits, it also poses several issues that impact its integration in education. Issues related to the trustworthiness of AI-generated information continue to be a major concern, particularly with respect to hallucinations and biases (Krishnan, 2025). This can impact the veracity of information, particularly in educational settings where the validity of information is paramount. Furthermore, the accessibility of AI may lead to misuse and overreliance, which could limit students' cognitive effort and the development of critical thinking skills. These concerns underline that GenAI's positive outcomes are far from guaranteed and are contingent on its use in learning.

These advances indicate that to comprehend the effects of GenAI in higher education, we need to go beyond usage-based explanations. Merely having access to AI tools is important, but interactions determine learning outcomes. As such, interaction becomes a key process in AI-supported learning, but its impact relies on how learners perceive, appraise, and use AI outputs. This suggests that there are underlying mechanisms that affect how interaction leads to outcomes, especially psychological ones such as trust. As such, this next section explores the mechanisms of interaction and their role in learning with AI.

Trust as a Mediating Mechanism in AI-supported Learning

Trust has increasingly been recognized as an important element shaping the relationship between generative artificial intelligence (GenAI) and learning outcomes in higher education. With the growing use of AI systems for academic purposes, students must assess the trustworthiness, reliability and value of AI-based tools and resources. Such evaluations influence whether learners choose to adopt, rely on, and effectively incorporate AI technologies into their academic activities.

One aspect of this process is epistemic trust, or learners' confidence in the truth and reliability of the knowledge produced by AI. Empirical studies indicate that trust can be shaped by perceptions of the reliability and performance of the system (Cui et al., 2025). The perceived reliability of AI-generated information increases the likelihood of students interacting with the system, incorporating the information to complete their academic tasks and achieving valuable learning outcomes. Likewise, the user experience and perceived benefits also foster trust and promote ongoing engagement with AI-enhanced learning platforms (Xiaoyu et al., 2025).

Crucially, trust plays a mediating role between interaction and learning. Simply interacting with the AI system does not ensure effective learning; rather, its impact is transmitted through the level of trust that learners place in AI systems. Research shows that trust impacts cognitive and behavioral outcomes, affecting students' attitudes toward and use of AI-generated feedback (Alotaibi, 2025). Existing evidence suggests that trust conditions the connection between technology engagement and behavioral intentions, further underlining its significance in AI-supported learning environments (Zhang et al., 2026).

At the same time, trust also introduces a certain level of complexity to AI-mediated learning. Although increased trust fosters engagement and trust, too much trust can induce overreliance and diminish critical thinking skills. However, low levels of trust can hinder the use of AI tools, restricting the benefits that can be derived from AI. This ambivalent role supports the idea that trust is a key mechanism that explains both the positive and negative effects of GenAI use and the central link between interaction and learning.

Learning Outcomes, Trade-offs, and Heterogeneity in AI Use

The integration of generative artificial intelligence (GenAI) into higher education introduces gains in learning support alongside possible educational compromises. On the one hand, GenAI boosts learning efficiency, creativity and student engagement through customized and adaptive learning. Research findings demonstrate that AI-supported tools increase the ability of learners to organize information, generate new ideas, and become more involved in learning activities, leading to enhanced learning outcomes and learning satisfaction (Xie et al., 2025).

On the other hand, research has identified several potential dangers of overreliance on AI tools. Issues of dependence, reduced cognitive effort, and diminished critical thinking indicate that although AI may have a positive effect on short-term performance, it may curtail deeper learning if not used carefully (Roy, 2026). Specifically, excessive use of AI-based content may decrease learners' willingness to engage in self-directed reasoning and problem solving. Likewise, the convenience provided by GenAI may lead to an emphasis on efficiency rather than conceptual understanding (Tórrez Martínez, 2025).

These results suggest that there are trade-offs between efficiency and cognitive processing during AI-mediated learning. Crucially, such findings are not exclusively dependent on the use of AI but also on

how learners engage with AI tools. These findings suggest that the educational consequences of GenAI depend substantially on interaction quality and the way that trust develops during AI use.

Moreover, the impacts of GenAI vary among students. The literature indicates variations in usage and benefits across academic levels and genders. For example, postgraduate students engage in more strategic and research-oriented use of AI, whereas undergraduate students focus more on basic academic assistance. Gender-based differences in risk perception and usage behavior also play a role in outcome variability (Pramjeeth, 2025; Wen, 2025). These differences highlight the need to account for heterogeneity in AI-based learning and how multigroup analysis can be applied to understand differences in interaction, trust and outcomes among different student subgroups.

Conceptual Model and Hypotheses

The existing GenAI research in education has largely concentrated on adoption, performance, and feedback applications while giving comparatively less attention to the mechanisms through which learner–AI interaction produces educational outcomes. Much of the current research focuses on individual aspects such as AI use, feedback, or learning performance, without considering how these factors interact in a cohesive framework. This leaves little understanding of how interaction leads to such outcomes, including the role of psychological constructs such as trust (Agrawal, 2026). Alternatively, recent studies highlight the need for models that describe the link between interaction processes and desired outcomes and potential trade-offs in AI-mediated learning (Zhang et al., 2026).

The current study introduces a model that integrates human-AI interaction, trust and learning outcomes. In this model, GenAI interaction is anticipated to contribute to learning outcomes both directly and indirectly through trust. It also includes task-oriented use as an element given that it is used to enhance learning by supporting academic tasks. It is assumed that trust is a key mediating factor that shapes both positive outcomes, such as learning enhancement, and negative outcomes, including potential trade-offs.

For clarity and consistency, the following constructs are referred to throughout the paper: the nature of interaction as interaction, GenAI across academic tasks as task-oriented use, *Trust & Transparency* as trust, and *Trade-offs & Risks* as trade-offs. On the basis of the preceding discussion and the identified gaps in understanding how human–GenAI interaction translates into learning outcomes, particularly through trust and associated trade-offs, this study addresses the following research questions:

RQ1 In what ways does human–GenAI interaction affect learning outcomes in higher education?

RQ2 To what extent does trust mediate the relationship between human–GenAI interaction and learning outcomes?

RQ3 How does task-oriented use of GenAI contribute to learning enhancement?

RQ4 How does trust simultaneously shape positive learning outcomes and perceived trade-offs in GenAI-supported learning?

RQ5 Do these relationships differ across academic level and gender?

Prior research indicates that generative AI impacts learning outcomes both directly and indirectly via psychological factors such as trust, perceived usefulness, and learner reliance. Existing studies also show that trust plays a central role in determining how students interpret, evaluate, and apply AI-generated outputs in academic contexts. Moreover, the more an AI system is relied upon, the more learning trade-offs that may exist, such as reduced cognitive engagement and excessive reliance. Drawing on the preceding theoretical discussion and identified research gaps, the study proposes the following hypotheses:

H1 Human–AI interaction positively influences trust in generative AI.

H2 Human–AI interaction positively influences learning enhancement.

H3 Task-oriented use positively influences learning enhancement.

H4 Trust positively influences learning enhancement.

H5 Trust influences learning trade-offs.

H6 Trust acts as a mediating mechanism linking interaction and learning outcomes.

Methodology

Participants and Procedure

A quantitative cross-sectional approach was employed to examine associations among human–GenAI interaction, trust formation, learning enhancement, and perceived trade-offs within higher-education settings. This study adopted a survey methodology, which is commonly used in educational technology studies, to understand students' perceptions and behaviors in technology-based learning (Han & Guo, 2025; Wang et al., 2025).

Data collection relied on an anonymous online questionnaire distributed to higher-education students regarding their experiences and perceptions of generative AI in their learning environment. The study obtained 237 valid responses from students enrolled in higher education institutions across India, primarily from the southern states of Tamil Nadu and Karnataka. The survey was circulated online through academic contacts and institutional networks via a convenience sampling strategy. Participation was voluntary, anonymous, and based on informed consent obtained prior to data collection.

Table 1 summarizes the demographic characteristics of the participants. Undergraduate students formed the largest subgroup within the sample (62.9%), followed by postgraduate students (30.4%), with

comparatively smaller representation from research scholars and academicians. The highest percentage of respondents (73.8%) were students from commerce and business-related disciplines, followed by science, engineering and IT-related fields (15.2%), and arts, humanities and social sciences (10.1%). With respect to the age group, the majority (52.7%) were aged between 17 and 20 years, whereas 37.1% were aged between 21 and 25 years. The gender composition of the sample included 54.9% male respondents and 44.7% female respondents. A large proportion of participants were enrolled in private/autonomous institutions and deemed universities. With respect to prior experience with AI tools, 46.8% reported less than six months of experience, whereas 32.1% reported more than one year of experience using AI tools.

Table 1
Demographic profile of the respondents

Characteristic	Category	Frequency	Percentage
Level of study	Undergraduate	149	62.9
	Postgraduate	72	30.4
	Research Scholar	9	3.8
	Academician	6	2.5
	Other	1	0.4
Gender	Male	130	54.9
	Female	106	44.7
	Prefer not to say/Other	1	0.4
Age group	17–20	125	52.7
	21–25	88	37.1
	26–35	20	8.4
	Above 35	4	1.7
Field of study	Commerce/Business	175	73.8
	Science/Engineering/IT	36	15.2
	Arts/Humanities/Social Sciences	24	10.1
	Other	2	0.8
Type of institution	Private/Autonomous	136	57.4
	Deemed University	88	37.1
	Public (Government/Aided)	11	4.6
	Other	2	0.8
Prior experience with AI tools	Less than 6 months	111	46.8
	6–12 months	50	21.1
	More than 1 year	76	32.1

Instrument

The measurement instrument was developed and adapted from established constructs in the literature on AI-supported learning and human–GenAI interaction. Human-AI interaction was captured by items

that reflected the intensity, extent, and engagement of student interaction with generative AI systems, as has been reported in previous studies that highlight interaction as a key mechanism in AI-based learning (Holmes, 2019). Task-oriented use reflects the degree to which students engage GenAI in specific learning tasks, such as writing, problem solving, and content creation, in line with its role in assisting learning (Farrokhnia et al., 2026). The survey also featured questions addressing the students' usage patterns of generative AI in various academic activities, such as assignment preparation, summarization, problem solving, exam preparation, and conceptual understanding.

Trust in generative AI was conceptualized as students' perceptions of the reliability, transparency, and credibility of AI-generated outputs. Earlier studies recognized trust as an important psychological dimension influencing AI adoption and its educational outcomes (Wang et al., 2025). We defined learning outcomes as learning enhancements and learning trade-offs. Learning enhancement was measured in terms of perceived improvement in academic performance, motivation and self-efficacy, and learning trade-offs were measured in terms of concerns about overreliance, reduced critical thinking, and superficial learning, as identified in previous studies on AI usage in education.

The survey instrument was structured into several sections. The first section collected respondents' demographic and academic details, including level of study, discipline, age group, gender, institutional type, and prior exposure to AI tools. The major constructs of the study were measured via five-point Likert-scale items ranging from 1 = strongly disagree to 5 = strongly agree, a widely used method in measuring perceptions and attitudes in educational research.

- Section B (B1–B4) measured the nature of interaction with generative AI.
- Sections C1–C9 explore the impact of generative AI on academic work, including assignment preparation, summarization, problem solving, preparation for examinations, and conceptual understanding.
- Section D (D1–D5) evaluated the perceived effectiveness of generative AI interaction.
- Sections E1–E5 measured motivation, self-efficacy, and academic engagement.
- Section F (F1–F6) is dedicated to examining the trust, transparency, and confidence in AI-generated content.
- Section G (G1–G5) examine the perceived trade-offs and risks associated with generative AI usage.
- Sections H1–H5 assess the quality of interaction and feedback experience.
- Section I (I1–I2) included overall reflections regarding generative AI-supported learning.

Human-GenAI interaction was conceptualized on the basis of students' intensity, extent, and interaction with generative AI systems. Task-oriented use refers to how students utilize generative AI for specific academic tasks, including tasks such as writing, content creation, conceptual understanding, and problem solving. The concept of trust in generative AI involves students' trust and confidence in the reliability, transparency, and trustworthiness of AI-generated content. Two dimensions were used for conceptualizing learning outcomes: learning enhancement and learning trade-offs. Perceived academic

performance, motivation, and self-efficacy were identified as aspects of learning enhancement, whereas superficial learning, reduced critical thinking, and overreliance were identified as learning trade-offs. In addition to the quantitative outcomes, the survey also featured open-ended reflections of students' experiences of generative AI in learning contexts to offer illustrative qualitative insights.

Data Analysis

The data were analyzed via structural equation modeling (SEM) in R (version 4.5.1) through RStudio (version 2025.09.0 + 387). Prior to structural analysis, descriptive statistics and normality assessment were conducted using the mean, standard deviation, skewness, and kurtosis values. The suitability of the data for factor analysis was evaluated via the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity. Exploratory factor analysis with parallel analysis was performed to confirm the factor structure.

Following the preliminary analysis, a two-step SEM procedure was employed. Assessment of the measurement model focused on internal consistency, convergent adequacy, and discriminant performance via established SEM diagnostics (Henseler et al., 2015). Internal consistency reliability was examined via Cronbach's alpha and composite reliability (CR), whereas convergent validity was assessed via average variance extracted (AVE). Discriminant validity was evaluated via the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT).

The structural model was then estimated to test the hypothesized relationships among the constructs. Model fit was evaluated via standard fit indices, including the comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). The explanatory power of the model was examined via coefficient of determination (R^2) values, and effect sizes (f^2) were calculated to assess the relative importance of the predictors. To test the indirect effect of interaction on learning outcomes through trust, mediation analysis was undertaken following the standard SEM analysis approach. Bootstrapping procedures were applied to assess the significance of indirect effects and mediation relationships.

To address potential methodological concerns, common method bias was assessed via Harman's single-factor test, and the robustness of the model was examined via comparisons of maximum likelihood (ML) and robust maximum likelihood (MLR) estimators. Furthermore, multigroup analysis was conducted across academic level, gender, and AI usage groups to examine potential differences in structural relationships across respondent categories. This methodological approach enables a comprehensive examination of the relationship between human–GenAI interactions and learning outcomes while also capturing the simultaneous role of trust in influencing beneficial learning outcomes as well as perceived educational trade-offs.

Results

Descriptive Statistics and Data Screening

The analysis was conducted via responses obtained from 237 higher education students. Table 2 provides descriptive statistics and normality assessment of all the measurement items. These findings reveal that the mean values range between 3.148 and 3.696, which implies that there is a moderate to relatively high level of agreement among respondents across constructs.

Table 2

Descriptive Statistics and Normality Assessment

No.	Variables	Mean	SD	Kurtosis	Skewness
1.	**Nature of Interaction**	**3.696**	**1.154**	**-0.86**	**0.162**
	B1	**3.506**	**1.137**	**-0.592**	**-0.127**
	B2	**3.418**	**1.115**	**-0.378**	**-0.253**
	B3	**3.502**	**1.167**	**-0.523**	**-0.323**
	B4				
2.	GenAI Across Academic Tasks	3.257	1.119	-0.009	-0.856
	C1	3.376	1.142	-0.221	-0.791
	C2	3.43	1.168	-0.198	-0.942
	C3	3.439	1.128	-0.228	-0.702
	C4	3.148	1.193	0.014	-0.888
	C5	3.224	1.223	-0.126	-0.974
	C6	3.224	1.185	-0.086	-0.897
	C7	3.224	1.137	-0.047	-0.851
	C8	3.207	1.133	0.009	-0.806
	C9				
3.	Perceived Effectiveness	3.515	1.122	-0.511	-0.33
	D1	3.481	1.007	-0.494	0.054
	D2	3.595	1.056	-0.539	-0.16
	D3	3.506	1.068	-0.422	-0.384
	D4	3.485	1.076	-0.541	-0.091
	D5				
4.	Motivation & Self-Efficacy	3.321	1.028	-0.411	-0.098
	E1	3.456	1.018	-0.563	0.09
	E2	3.363	1.043	-0.36	-0.243
	E3	3.574	1.029	-0.453	-0.227
	E4	3.456	1.039	-0.447	-0.217
	E5				

No.	Variables	Mean	SD	Kurtosis	Skewness
1.	**Nature of Interaction**	**3.696**	**1.154**	**-0.86**	**0.162**
	B1	**3.506**	**1.137**	**-0.592**	**-0.127**
	B2	**3.418**	**1.115**	**-0.378**	**-0.253**
	B3	**3.502**	**1.167**	**-0.523**	**-0.323**
	B4				
5.	Trust & Transparency	3.203	0.996	-0.155	-0.228
	F1	3.363	0.922	-0.29	0.028
	F2	3.3	0.974	-0.185	-0.169
	F3	3.527	1.027	-0.459	-0.009
	F4	3.633	1.019	-0.396	-0.415
	F5	3.506	0.977	-0.221	-0.114
	F6				
6.	Trade-offs & Risks	3.46	1.043	-0.306	-0.3
	G1	3.574	1.029	-0.337	-0.351
	G2	3.464	1.043	-0.317	-0.125
	G3	3.435	1.021	-0.323	-0.205
	G4	3.443	1.063	-0.379	-0.137
	G5				
7.	Interaction Quality	3.329	1.07	-0.369	-0.199
	H1	3.43	0.983	-0.326	0.057
	H2	3.418	1.02	-0.374	-0.056
	H3	3.485	0.946	-0.346	0.321
	H4	3.473	0.968	-0.467	0.23
	H5				
8.	Overall Reflection	3.506	1.08	-0.479	-0.151
	I1	3.502	1.048	-0.379	-0.106
	I2				

SD standard deviation. B1–B4 represent items measuring the nature of interaction with generative AI; C1–C9 represent GenAI use across academic tasks; D1–D5 represent perceived effectiveness; E1–E5 represent

motivation and self-efficacy; F1–F6 represent trust and transparency; G1–G5 represent perceived trade-offs and risks; H1–H5 represent interaction quality; and I1–I2 represent overall reflections on GenAI-supported learning. The absolute skewness and kurtosis values were within acceptable limits for SEM analysis.

The descriptive statistics are presented according to the initial measurement dimensions. In the subsequent measurement and structural models, several related dimensions were integrated into broader latent constructs, including interaction, enhancement, trust, task-oriented use, and trade-offs, on the basis of the conceptual framework and factor structure. All the values of standard deviation are within an acceptable range, which implies that there is a reasonable variability in the responses. The skewness and kurtosis values fall within the recommended thresholds of ± 2, indicating that the data are not significantly out of normality. These findings indicate that the data can be used to conduct additional multivariate analyses, such as structural equation modeling.

Measurement Model

To determine the reliability and validity of the constructs and guarantee the suitability of the data for structural equation modeling, the measurement model was evaluated. The Kaiser–Meyer–Olkin (KMO) measure and the Bartlett test of sphericity were first used to test sampling adequacy. Table 3 indicates that the KMO value of 0.950 is greater than the recommended value of 0.70, which is excellent sampling adequacy. The test of sphericity by Bartlett was significant ($\chi^2 = 8444.61$, $df = 861$, $p < 0.001$), which means that the data are suitable for analysis via factor analysis.

Table 3
Sampling adequacy and Bartlett's test of sphericity

Test	Statistic	Value
Kaiser–Meyer–Olkin (KMO)		0.950
Bartlett's Test of Sphericity	χ^2	8444.61 861
	df	< 0.001
	Sig.	

KMO Kaiser–Meyer–Olkin

A parallel analysis was used to conduct the exploratory factor analysis to investigate the underlying factor structure. Exploratory factor analysis supported the integration of conceptually related dimensions into broader latent constructs. In particular, perceived effectiveness, motivation and self-efficacy, overall reflection, and interaction quality demonstrated substantial conceptual overlap with the enhancement-related dimensions and were therefore incorporated into the broader construct structure used in the final SEM.

The eigenvalues of the actual data and those of the simulated data are greater than those of the first five factors, as shown in Fig. 1, which supports the five-factor solution proposed by the conceptual model.

Factor loadings, Cronbach's alpha, composite reliability (CR) and average variance extracted (AVE) were used to determine the reliability and convergent validity of the constructs. As presented in Table 4, all factor loadings exceed the recommended threshold of 0.60, which is a good indicator of item reliability (Hair et al., 2010). The Cronbach's alpha values are between 0.885 and 0.948, and the composite reliabilities are between 0.884 and 0.947, which is greater than the threshold of 0.70, a test of internal consistency. The AVE values range from 0.561–0.664, which are greater than the value of 0.50 and indicate that convergent validity is satisfactory (Kline, 2023).

Table 4

Reliability and convergent validity

Construct	Item	Factor Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Nature of Interaction	B1	0.862	0.909	0.908	0.664
	B2	0.869			
	B3	0.789			
	B4	0.803			
	B5	0.747			
GenAI Across Academic Tasks	C1	0.788	0.944	0.945	0.656
	C2	0.793			
	C3	0.749			
	C4	0.782			
	C5	0.799			
	C6	0.883			
	C7	0.812			
	C8	0.808			
	C9	0.860			
Trust & Transparency	F1	0.700	0.885	0.884	0.561
	F2	0.745			
	F3	0.705			
	F4	0.791			
	F5	0.801			
	F6	0.737			
Enhancement	D1	0.829	0.948	0.947	0.600
	D2	0.794			
	D3	0.843			
	D4	0.837			
	D5	0.799			
	E1	0.697			
	E2	0.835			

Construct	Item	Factor Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
	E3	0.748			
	E4	0.804			
	E5	0.776			
	I1	0.664			
	I2	0.636			
Trade-offs & Risks	G1	0.777	0.900	0.900	0.643
	G2	0.820			
	G3	0.822			
	G4	0.823			
	G5	0.769			

Both the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT) were used to measure discriminant validity (Henseler et al., 2015). As indicated in Table 5, the square root of the AVE of each construct typically has higher values than the correlations between that construct and others. Although the correlation between Trust and Enhancement is relatively high, this fact is theoretically acceptable because of the conceptual proximity of these two concepts. All the values of the HTMT are lower than the conservative value of 0.85, which shows that discriminant validity is achieved to a satisfactory degree.

Table 5
Discriminant validity

Fornell–Larcker					
Construct	**NOI**	**GAAT**	**TT**	**ENH**	**TOR**
NOI	**0.815**				
GAAT	0.667	**0.81**			
TT	0.623	0.416	**0.749**		
ENH	0.743	0.641	0.789	**0.765**	
TOR	0.418	0.278	0.67	0.581	**0.802**
HTMT Ratio					
Construct	**NOI**	**GAAT**	**TT**	**ENH**	**TOR**
NOI	-				
GAAT	0.304	-			
TT	0.503	0.176	-		
ENH	0.571	0.271	0.772	-	
TOR	0.433	0.107	0.697	0.726	-

NOI Nature of Interaction, GAAT GenAI Across Academic Tasks, TT Trust and Transparency, ENH Enhancement, TOR Trade-offs and Risks, HTMT Heterotrait–Monotrait Ratio. The square roots of AVE are shown in bold on the diagonal.

Table 6
Harman's single-factor test for common method bias

Factor	**Eigenvalue**	**Variance Explained (%)**
Single factor	19.15	45.60

A Harman single-factor test was performed to determine the possibility of potential common method bias. Table 6 indicates that the first factor explains 45.6% of the total variance, which is less than the recommended threshold of 50%, indicating that the issue of common method bias is unlikely to be a serious concern.

Structural Model

The structural model was evaluated to examine the hypothesized relationships among the constructs, as shown in Table 7. The model fit indices suggest an acceptable fit to the data, with CFI = 0.869, TLI = 0.860, RMSEA = 0.080 and SRMR = 0.078, all within acceptable ranges of structural equation modeling.

Table 7
Model fit indices

Fit Index	Value
Comparative Fit Index (CFI)	0.869
Tucker–Lewis Index (TLI)	0.860
Root Mean Square Error of Approximation (RMSEA)	0.080
Standardized Root Mean Square Residual (SRMR)	0.078

The model demonstrates an acceptable fit to the data on the basis of standard SEM thresholds.

The results of the hypothesis testing are shown in Table 8, and the structural model is illustrated in Fig. 2. The findings indicate that interaction has a strong positive effect on trust (H1: $\beta = 0.623$, $p < 0.001$), meaning that the stronger the human-GenAI interaction is, the better the level of trust in generative AI systems. Conversely, trust has a significant positive effect on Enhancement (H2: $\beta = 0.533$, $p < 0.001$), which shows its key role in enhancing learning outcomes.

Table 8
Structural Model Results (Hypothesis Testing)

Hypothesis	Path	Path coefficient (β)	SE	z value	p value	Result
H1	Interaction → Trust	0.623	0.068	9.11	< 0.001	Supported
H2	Trust → Enhancement	0.533	0.074	7.23	< 0.001	Supported
H3	Interaction → Enhancement	0.235	0.083	2.85	0.004	Supported
H4	Task → Enhancement	0.262	0.071	3.69	< 0.001	Supported
H5	Trust → Tradeoff	0.670	0.072	9.27	< 0.001	Supported

SE standard error. All the hypothesized relationships were statistically significant.

Int Interaction, Trs Trust, Tsk Task-oriented use, Enh Enhancement, Trd Tradeoffs.

Moreover, interaction has a direct effect on Enhancement (H3: $\beta = 0.235$, $p = 0.004$), which implies that interaction contributes to learning outcomes beyond its indirect effect through trust. Task-oriented use also has a significant positive influence on Enhancement (H4: $\beta = 0.262$, $p < 0.001$), which means that the academic use of generative AI in a structured manner positively influences learning performance.

Furthermore, Trust has a strong positive effect on Trade-offs (H5: β = 0.670, p < 0.001), indicating that increased reliance on generative AI may also be associated with greater perceived risks or trade-offs in learning.

Table 9
Coefficient of determination (R^2)

Endogenous Construct	R^2
Trust	0.389
Enhancement	0.764
Tradeoff	0.448

R^2 represents the proportion of variance explained in each endogenous construct.

The explanatory power of the model is substantial. As shown in Table 9, interaction explained 38.9% of the variance in Trust (R^2 = 0.389), and interaction, task-oriented use, and Trust together explained 76.4% of the variance in Enhancement (R^2 = 0.764). Trust also contributes to 44.8% of the variance in Trade-offs (R^2 = 0.448), which shows that the explanatory power of endogenous constructs is moderate to strong.

Mediation Analysis

To investigate the mediating effect of Trust on the relationship between Interaction and Enhancement, a mediation analysis was undertaken by bootstrapping procedures. According to the results, the indirect effect of interaction on enhancement through trust is significant (β = 0.333, z = 3.84, p < 0.001), as presented in Table 10. The total effect of interaction on enhancement is also found to have a significant effect (β = 0.568, p < 0.001), indicating that interaction plays an important role in shaping learning outcomes.

Table 10
Indirect and Total Effects (Mediation Results)

Indirect Effect Estimation					
Indirect Path	**Estimate**	**Std.Err**	**z value**	**p value**	**Std.all**
Interaction → Trust → Enhancement	0.684	0.178	3.84	< 0.001	0.333

Total Effect					
Path	**Estimate**	**Std.Err**	**z value**	**p value**	**Std.all**
Interaction → Enhancement	1.167	0.258	4.52	< 0.001	0.568

Std.Err standard error, Std.all standardized effect

Notably, the direct impact of interaction on enhancement remains significant (β = 0.235, p = 0.004), which indicates the existence of partial mediation. This implies that Trust is a major mechanism through which human–GenAI interaction affects learning enhancement, in addition to the possibility of a direct effect of the interaction.

Table 11
Nested Model Comparison

Model	df	χ^2	AIC	BIC
Full mediation model	622	1568.94	19967.22	20248.13
Restricted model	623	1651.03	20047.31	20324.76

AIC Akaike information criterion, BIC Bayesian information criterion

Table 12
Chi-square difference test

Comparison	$\Delta\chi^2$	Δdf	p value
Full model vs Restricted model	82.09	1	< 0.001

To further validate the mediation structure, a comparison of the nested model was conducted between the full model and the restricted model that omitted the mediation path. As shown in Tables 11 and 12, the chi-square difference test suggests that the full model is a significantly better fit than the restricted model ($\Delta\chi^2 = 82.09$, $\Delta df = 1$, $p < 0.001$), which supports the robustness of the mediation effect.

Effect size

The effect sizes (f^2) were computed to determine the practical significance of the structural relationships within the model. (Cohen, 1988) argues that f^2 values of 0.02, 0.15, and 0.35 represent small, medium and large effects, respectively. The effect sizes of the structural paths are given in Table 13.

Table 13
Effect size (f^2) of structural paths

Structural Path	f^2 Value	Effect Size Interpretation
Interaction → Trust	0.64	Very Large
Trust → Enhancement	0.51	Large
Trust → Trade-offs	0.81	Very Large
Interaction → Enhancement	0.08	Small
Task → Enhancement	0.07	Small

*f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively (*Cohen, 1988*).*

The findings show that the effect of interaction on trust is very large ($f^2 = 0.64$), which implies that the quality of the human–GenAI interaction is a strong determinant of trust formation. The effects of Trust on Enhancement ($f^2 = 0.51$) and Trade-offs ($f^2 = 0.81$) are large and very large, respectively, which shows that Trust has a substantial influence on both positive and negative learning outcomes.

In contrast, the direct effects of interaction on enhancement ($f^2 = 0.08$) and task-oriented use on enhancement ($f^2 = 0.07$) are small, which implies that the independent effects of the two factors on learning outcomes are relatively weak. These findings suggest that Trust has the greatest impact in the model compared with other structural relationships.

Robustness Checks

To determine the robustness of the structural model, the analysis was re-estimated with the help of both maximum likelihood (ML) and robust maximum likelihood (MLR) estimators. The model fit indices of the two estimation methods are represented in Table 14.

Table 14
Model fit comparison: ML vs. *MLR estimators*

Fit Index	**ML**	**MLR**
χ^2 (Chi-square)	1568.94	1235.19
df	622	622
CFI	0.869	0.889
TLI	0.860	0.881
RMSEA	0.080	0.073
SRMR	0.078	0.078

ML maximum likelihood, MLR robust maximum likelihood, CFI comparative fit index, TLI Tucker–Lewis index, RMSEA root mean square error of approximation, SRMR standardized root mean square residual

The findings show that there is a slight improvement in model fit when the MLR estimator is used, with higher values of CFI (0.889 vs. 0.869) and TLI (0.881 vs. 0.860), as well as a lower RMSEA (0.073 vs. 0.080). The values of SRMR are the same for both estimators. These results indicate that the model can withstand possible deviations of normality and that the structural relationships do not change when there are different methods of estimation.

Multigroup Analysis

The heterogeneity in terms of academic level, gender, and AI usage was investigated via multigroup analysis.

Table 15
Multi-Group Model Comparison

Grouping Variable	Δχ²	Δdf	p value	Interpretation
UG vs PG	15.668	5	0.008	Significant
Gender	16.652	5	0.005	Significant
AI Usage	8.459	5	0.133	Not significant

UG undergraduate students, PG postgraduate students

Table 16
Groupwise Standardized Path Coefficients

Path	UG	PG	Female	Male
Interaction → Trust	0.372	0.587	0.550	0.449
Trust → Enhancement	0.478	0.521	0.413	0.614
Interaction → Enhancement	0.258	0.241	0.373	0.120
Task → Enhancement	0.359	0.224	0.245	0.252
Trust → Tradeoff	0.437	0.629	0.554	0.583

UG undergraduate students, PG postgraduate students. Values represent standardized path coefficients.

The results of the multigroup model comparison are shown in Table 15. Notable differences were found in terms of academic level ($\Delta\chi^2 = 15.668$, $\Delta df = 5$, $p = 0.008$) and gender ($\Delta\chi^2 = 16.652$, $\Delta df = 5$, $p = 0.005$), which means that the structure of the relationships is not the same across these groups. Conversely, there was no significant difference among the levels of AI use ($\Delta\chi^2 = 8.459$, $\Delta df = 5$, $p = 0.133$), which indicates that the structural relationships are maintained without changes in the level of AI use.

The standardized path coefficients across groups are provided in Table 16. The findings suggest that postgraduate students exhibit stronger effects of interaction on trust and trust in trade-offs than undergraduate students do, whereas undergraduate students show relatively stronger effects of task-oriented use on enhancement. With respect to gender, the interaction-based effects among female students are stronger, whereas the trust-driven pathways among male students are more pronounced.

Illustrative qualitative insights

The survey also included an open-ended question and one descriptive perception question regarding students' experiences with generative AI in learning to complement the quantitative results. All 237 participants responded to the descriptive perception item, and 121 of the respondents answered the open-ended question voluntarily. Although these responses were not formally analyzed as a qualitative

component, they provide illustrative insights into students' perceptions of interaction with AI-supported learning environments.

Among the 237 respondents, 41.8% reported that generative AI had a significant impact on the way in which they learned and worked academically, and 28.7% indicated that it had a moderate impact. An additional 17.7% reported that it had a slight impact, and only a small proportion indicated that it had little or no impact or "rarely used" generative AI.

A number of the students described that generative AI was a useful tool that aided their learning in the following ways: more efficient learning, making a difficult concept easier to grasp, helping with assignment preparation, and increasing their confidence in learning. A few respondents highlighted that AI-assisted interaction helped them overcome hesitation in asking questions, organize ideas more effectively, and participate in academic tasks more actively. One respondent noted that "it feels like having a tutor available anytime to clear doubts without hesitation." Some respondents reported that they felt that AI offered convenient and constant help with their doubts without hesitation, whereas others stated that it allowed them to understand difficult concepts quickly and structure assignments more efficiently. The quantitative results are confirmed by these observations: interaction and trust positively influence learning enhancement.

Moreover, some responses reflected excessive dependence on AI, reduced independent thinking, and decreased creativity. Students said that relying too heavily on AI could undermine cognitive engagement and effort for deeper learning. One respondent stated that "it makes everyone lazy rather than learn something additionally," whereas another observed that "AI took over creativity." The perceptions are quite similar to the study's findings concerning trade-offs in learning and strengthen the dual role of trust identified in the structural model.

Overall, the qualitative responses provide additional support for the study's central argument that the extent to which generative AI is effective in higher education extends beyond the amount that it is used but rather extends beyond the quality of interaction and the manner in which trust is developed in generative AI-supported learning environments.

Discussion

Interaction and Trust as the Core Mechanisms

The results support the hypotheses presented and offer answers to research questions related to the effects of the human-GenAI interaction on learning outcomes, including aspects of trust and task-oriented use. This paper indicates that the relationship between human-GenAI interaction and the outcomes of learning is motivated mainly by the element of trust, as opposed to direct effects. Although interaction has a significant positive influence on learning enhancement, its direct impact is relatively small, meaning that interaction by itself cannot produce meaningful learning outcomes. Rather, the

success of interaction is determined by the interpretations, assessments, and incorporation of AI-generated outputs in the learning process of the learner.

This observation supports the transformation of a tool-focused approach to the interaction-focused approach to the learning process with AI assistance. Past studies indicate that the value of generative AI can be due not only to the availability of tools but also to the quality of interaction and engagement with tools (Gabay et al., 2026; Wang et al., 2025). Trust in this scenario is a key psychological process that translates interaction into learning outcomes that are meaningful.

This is further supported by the illustrative qualitative responses. Many students reported that generative AI supported them in better comprehending and understanding complex concepts, managing their assignments better, and approaching academic tasks with greater confidence. Another few respondents commented on how the use of AI in interactions minimized their hesitation to pose questions and helped provide more personalized learning experiences, reinforcing the importance of the quality of interaction in shaping educational outcomes.

The findings also indicate that interaction strongly influences trust, which in turn significantly enhances learning outcomes. This confirms the findings of prior studies that perceived reliability, usefulness, and user experience influence the development of trust in AI systems and are at the heart of deciding whether learners accept and successfully use AI-generated outputs (Cui et al., 2025; Zhang et al., 2026). In this way, interaction can affect learning indirectly, i.e., through the development of trust, which points to the significance of relational and cognitive processes within the context of the learning process mediated by AI.

Trust as a Double-Edged Mechanism: Enhancement vs Trade-offs

A key contribution of this research is the identification of the dual-impact mechanism of trust that contributes to both learning enhancement and trade-offs. The results show that trust positively impacts learning enhancement activities with a high level of significance, which means that if learners believe that AI systems are reliable and useful, they tend to immerse themselves in AI-based learning activities. This finding is in line with those of previous studies indicating that trust positively contributes to motivation, self-efficacy, and engagement in digital learning environments (Cui et al., 2025; Wang et al., 2025).

Nonetheless, the findings also indicate that trust significantly positively impacts trade-offs in learning. This means that increased trust can result in more reliance on AI systems, which can decrease critical thinking, the ability to solve problems independently, and more profound cognitive engagement. This twofold effect underscores the multifaceted nature of AI-supported learning, in which the same mechanism that facilitates the provision of learning benefits can be a source of risk. Several students

similarly voiced their concerns about reliance on AI and the reduction of independent thinking, thereby indicating that learning trade-offs were present in the structural model.

This observation extends the literature, which has centered mostly on the advantages of generative AI by demonstrating the simultaneous presence of both positive and negative results in the same paradigm in an empirical way. This finding supports recent studies that caution against the excessive use of AI, which implies that efficiency gains can be achieved at the cost of more profound learning mechanisms (Roy, 2026; Tórrez Martínez, 2025).

Importantly, this dual role of trust is a direct reaction to the call to research trade-offs in AI-mediated learning, as it indicates that the increase in learning results does not depend on the possible costs. Trust, thus, cannot be seen as only a positive enabler but rather as an important mechanism that must be handled with care in an educational setting.

Heterogeneity and the Role of Usage

The multigroup analysis also provides some additional insight into how these relationships differ among the various groups of students. These results show a significant level of variation with academic level and gender, which suggests that interaction and trust have different mechanisms that affect learning outcomes among learners. An example is that postgraduate students tend to have stronger trust-related effects, whereas undergraduate students tend to depend on task-related use to enhance their learning.

These results are consistent with earlier studies that indicated that students vary in their interactions with AI systems depending on their experience, learning strategies, and contextual factors (Pramjeeth, 2025; Zhang et al., 2026). This heterogeneity underscores the need to consider the characteristics of learners when designing AI-based learning environments.

Conversely, there are no significant differences in the results across levels of AI usage. This implies that it is not how frequently students use AI that will define its learning outcomes but rather how frequently their interaction with it and the level of trust they develop. That is, usage intensity does not drive outcomes; interaction quality and trust are the key determinants.

This result challenges a common assumption in the literature that increased AI usage inevitably results in improved learning outcomes. Instead, it substantiates the opinion that meaningful interaction, rather than frequency of use, is the most important determinant of effective AI-aided learning (Mirzaei & Khayer, 2025; Xiaoyu et al., 2025).

From an educational perspective, this means that merely exposing more students to available AI tools or encouraging their more frequent utilization is unlikely to enhance learning outcomes. Rather, educators ought to aim at fostering high-quality interaction and educating students to respond effectively to AI systems critically.

Limitations and Future Research Directions

Despite offering several theoretical and practical insights, the study is subject to important limitations that should be acknowledged. The cross-sectional nature of the design limits causal interpretation of the relationships among interaction, trust, and learning outcomes. As emphasized in previous studies, the interaction between humans and AI is a dynamic process that develops through experience and acquaintance (Xiaoyu et al., 2025). Future studies might use longitudinal or experimental designs to gain more insight into how trust is built with time and how it influences learning in long-term AI-supported learning environments.

Second, the research is based on self-reported measures of interaction, trust, and learning outcome measures. Although these measures are typical of educational technology research, they are prone to response bias. As established in previous research, actual interaction with AI systems, especially the interaction of learners with feedback and optimization of the output, is an essential factor in the effectiveness of learning (Gabay et al., 2026). Subsequent studies might include behavioral information, such as interaction records or task-related performance indicators, to offer a more objective evaluation of AI usage.

Third, although some illustrative qualitative responses were included to complement the quantitative results, no formal qualitative design or thematic analysis was used. Future investigations could combine quantitative and qualitative designs to capture richer dimensions of students' experiences with GenAI interaction.

Fourth, although the present study analyzes heterogeneity on the basis of academic level and gender, other contextual factors were not taken into consideration. According to the literature, discipline, previous experience with AI, and the learning setting can play crucial roles in determining how students engage with AI systems and develop trust (Cui et al., 2025; Zhang et al., 2026). Future studies may build on this framework by introducing these contextual variables to offer a more comprehensive perspective on AI-mediated learning.

Finally, the sample is geographically concentrated in selected higher education institutes in southern Indian states of Tamil Nadu and Karnataka and is predominantly composed of students in commerce- and business-related disciplines. The regional and disciplinary concentration of the sample limits the transferability of the findings across broader educational settings. Future studies may expand the framework to other parts of the globe, other fields, and levels of education, such as school education and professional learning settings, to explore possible similarities in interaction–trust processes.

Implications for theoretical development and educational practices

The study contributes to ongoing higher-education GenAI scholarship by foregrounding interaction processes rather than adopting a purely tool-oriented perspective. Although previous studies have investigated the functional aspects of AI systems, including efficiency and productivity (Gabay et al., 2026), the current results reveal that the process of learning is affected by student-AI system

interactions and the way that trust is built in the process. By positioning trust as a central mediating mechanism, this study extends interaction-focused scholarship on GenAI learning processes and highlights the importance of psychological and relational dimensions in AI-supported education (Agrawal, 2026; Zhang et al., 2026). The results suggest that interaction does not suffice to generate significant learning effects; instead, its impacts are mediated by trust, which defines how learners perceive and use AI-generated outputs.

The findings further deepen the current understanding by demonstrating the dual function of trust within AI-supported learning. While trust enhances learning outcomes, including motivation, self-efficacy, and perceived effectiveness, it also increases the trade-offs in learning, such as overreliance, and decreases cognitive engagement. This finding is consistent with those of previous studies indicating that overreliance on AI can impair more in-depth learning and critical thinking (Roy, 2026; Tórrez Martínez, 2025). Notably, the results can be used to dispute the idea that the more AI is used, the more learning outcomes may be different. Rather, the findings indicate no significant change in the structural relationships due to the intensity of usage, which supports the notion that the quality of interaction and trust formation, and not the frequency of use, are the primary factors that drive educational outcomes.

The implications of these theoretical insights for educational practice are also important. The results show that merely having access to AI devices is not enough to enhance learning outcomes. Rather, the task of educators is to foster meaningful interaction with AI systems, with a focus on active engagement and critical evaluation of AI-generated outputs. Previous studies indicate that learning benefits are achieved when students work actively with the feedback generated by AI and refine their knowledge through iterative interaction (Mirzaei & Khayer, 2025; Wang et al., 2025; Xiaoyu et al., 2025). Consequently, instructional strategies must encourage the reflective use of AI instead of passive reliance.

The paramount purpose of trust also underscores the necessity of integrating AI literacy into the curriculum of higher education programs. Students should be equipped to assess the reliability and limitations of AI-generated content. Studies indicate that trust is shaped on the basis of perceptions of system reliability and usefulness and directly affects how learners engage with AI tools (Cui et al., 2025; Xiaoyu et al., 2025). The education interventions must thus be able to build calibrated trust, such that students do not over- or underuse AI systems.

Student reflections suggest that GenAI is perceived not only as an efficiency-enhancing instrument but also as a mechanism for confidence building, accessibility, and ongoing academic assistance. Moreover, worries about dependence and diminished cognitive engagement emphasize the need for balanced and pedagogically guided AI integration.

The identification of trade-offs highlights the importance of balanced AI integration. Although generative AI can enhance efficiency and performance, overdependence can decrease opportunities to reason independently and cognitive engagement. This confirms previous data that AI-enhanced efficiency may at times come at the expense of critical thinking and conceptual understanding (Roy, 2026; Tórrez

Martínez, 2025). Finally, the observed differences across academic level and gender suggest that AI-supported learning is not uniform across all student populations and suggest that an adaptive teaching strategy should be implemented. Moreover, the absence of differences across the levels of AI usage strengthens the argument that effective learning depends more on the use of AI than on the frequency of its use.

Conclusion

This study suggests that the effectiveness of GenAI in higher education does not rely on the number of times the technology is used but rather on the quality of the interaction and the development of trust. This paper provides further insight into how generative AI can be used to enhance learning as well as to create learning trade-offs by making trust a key process causing interactions leading to learning outcomes.

The results indicate that trust plays a dual role in AI-supported learning. On the one hand, it enhances the learning results, as it makes it more engaged, more motivated and more effective. Conversely, it is a contributor to the possibility of potential threats such as overreliance and reduced cognitive effort. This two-sidedness is mirrored in the multifacetedness of AI-mediated learning, as benefits and trade-offs coexist rather than operate independently (Roy, 2026; Tórrez Martínez, 2025).

The findings also show that variations in learning outcomes are driven not by the intensity of usage but rather by the way students interact with and build trust in AI systems. This underscores the role of the quality of interaction and psychological mechanisms in the development of effective learning with the use of AI. The student reflections in the illustrative section further reinforce that meaningful educational outcomes emerge when generative AI supports active engagement, conceptual understanding, and guided learning rather than passive dependence.

On the whole, the research adds to the current debate about human-AI interaction in higher education by demonstrating that meaningful learning outcomes emerge from the interplay between interaction, trust, and task-oriented use. These insights offer a foundation for developing more efficient, balanced, and pedagogically grounded approaches to incorporating generative AI into education.

Declarations

Ethics Declaration

Ethics Approval

This study involved an anonymous, non-interventional online questionnaire administered to adult higher education students. Participation was entirely voluntary, the study posed no more than minimal risk to participants, and no personally identifiable information, biological samples, or sensitive personal data were collected.

Ethical Conduct

All research procedures were conducted in accordance with the ethical principles of the World Medical Association Declaration of Helsinki (2013 revision), as applicable to non-interventional human participant research, together with the principles of responsible research conduct contained in the SRM Institute of Science and Technology Institutional Code of Ethics for Research and the SRM Institute of Science and Technology Research Policy.

Informed Consent

Electronic informed consent was obtained from all participants before participation through the introductory page of the online questionnaire. Participants were informed of the purpose of the study, that participation was entirely voluntary, that responses would remain anonymous, that no personally identifiable information would be collected, and that they could discontinue participation at any time before submitting the questionnaire. Completion and submission of the questionnaire constituted informed consent to participate in the study.

Footnote to the Ethics Declaration

Institutional Code of Ethics for Research

https://webstor.srmist.edu.in/web_assets/downloads/2023/institutional-code-of-ethics-and-research.pdf

Research Policy

https://www.srmist.edu.in/policies/research-policy/

Competing Interests

The authors declare that they have no competing interests.

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Author Contribution

A.P.M.: Conceptualization, Methodology, Data curation, Formal analysis, Investigation, Visualization, Writing – original draft, Writing – review & editing. G.D.: Conceptualization, Methodology, Supervision, Validation, Resources, Writing – review & editing. All authors reviewed and approved the final manuscript.

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Data Availability

The survey questionnaire, de-identified dataset, and R analysis script supporting the findings of this study have been provided as Supplementary Information accompanying this submission. The shared dataset contains no personally identifiable participant information and is provided in accordance with the ethical principles governing participant confidentiality.

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Figures

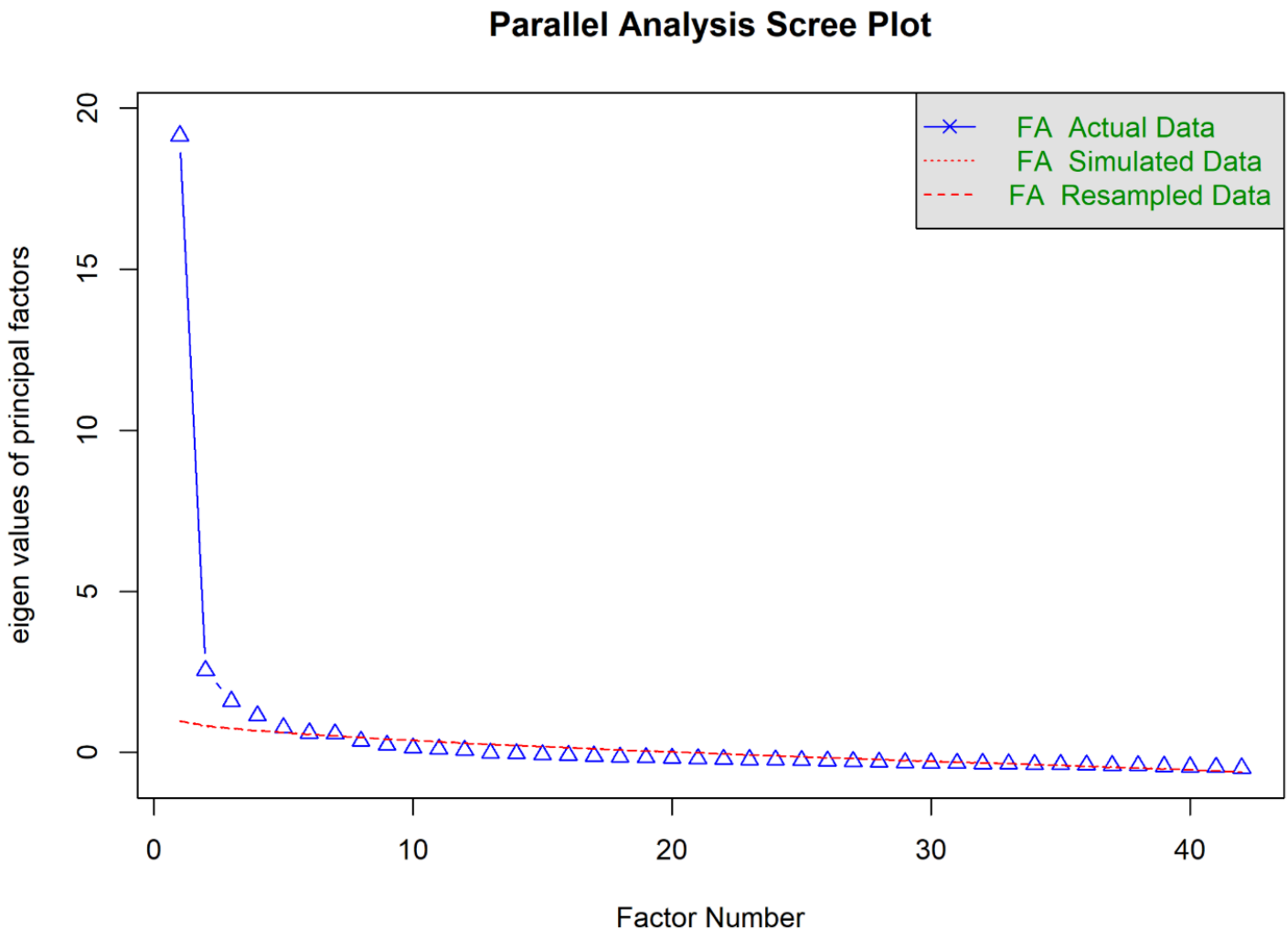


Figure 1

Parallel analysis scree plot

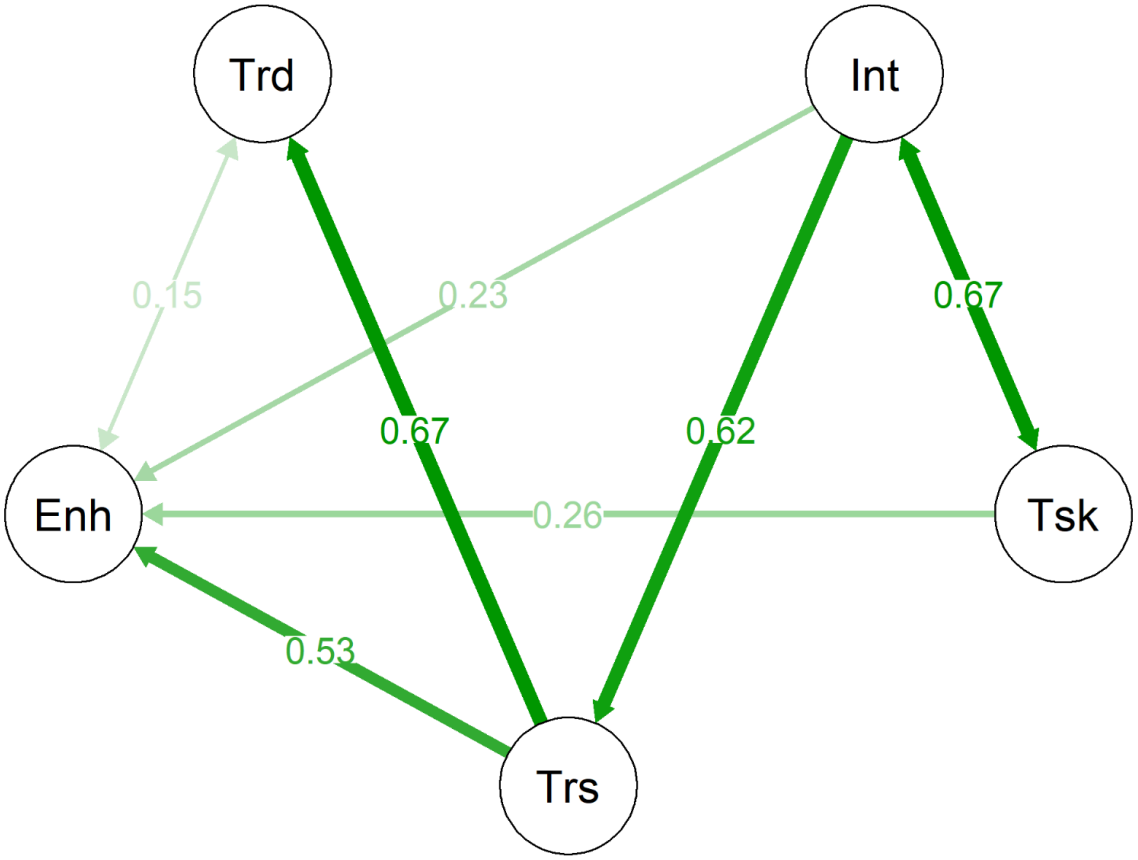


Figure 2

Structural model results

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryFile2Dataset.csv
- SupplementaryFile1Questionnaire.pdf
- SupplementaryFile3RCode.r