

Developing Epistemic Transparency in AI-Supported Higher Education: Roles of Prompt Literacy, Critical AI Literacy, and Assessment Design

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Abstract The rapid use of generative artificial intelligence (GenAI) in higher education has raised concerns about student responsibility, transparency, and meaningful learning. This study examines how prompt literacy, critical AI literacy, and assessment design contribute to epistemic transparency in AI-supported learning environments. A quantitative cross-sectional survey design was adopted. Data were collected from 649 undergraduate and postgraduate students enrolled in higher education institutions in India. Partial least squares structural equation modeling was employed to test the direct, indirect, and interaction effects. The results show that prompt literacy has a strong positive effect on critical AI literacy and a statistically significant but modest direct effect on epistemic transparency. Critical AI literacy further partially mediates the relationship between prompt literacy and epistemic transparency. Critical AI literacy and assessment design also exert significant positive direct effects on epistemic transparency, with assessment design demonstrating the strongest direct practical contribution. However, the interaction between assessment design and critical AI literacy is not significant, indicating that these factors operate independently in promoting transparent AI-supported learning. This study introduces epistemic transparency as a distinct and measurable learning outcome in AI-mediated higher education. By integrating student competencies with

assessment design, it offers practical insights for developing responsible and transparent AI use in higher education.

Keywords generative artificial intelligence (GenAI), higher education, AI literacy, assessment design, epistemic transparency, prompt literacy

1 Introduction

Generative artificial intelligence (GenAI), particularly large language models (LLMs)-powered tools such as ChatGPT, Copilot, and Gemini, has rapidly become embedded in higher education learning practices. Students now routinely use these tools for drafting assignments, clarifying concepts, generating examples, and receiving instant feedback (Baig & Yadegaridehkordi, 2024; Dempere et al., 2023). Research suggests that, when used appropriately, GenAI can support learning efficiency and higher-order thinking (Borge et al., 2024; Wang & Fan, 2025). However, beyond these benefits, scholars have raised serious concerns about academic integrity, overreliance, epistemic opacity, and diminished student accountability for AI-assisted work (Gruenhagen et al., 2024; Kasneci et al., 2023; Tight, 2024).

Much of the existing literature on GenAI in higher education focuses on adoption, perceived usefulness, and integrity violations (Abdallah et al., 2025; Johnston et al., 2024). While valuable, the literature

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often treats AI use as a technical or behavioral issue, paying limited attention to the epistemic processes through which students interact with AI, evaluate AI-generated outputs, and take responsibility for knowledge claims. Given that GenAI systems produce probabilistic and sometimes inaccurate responses, students must actively judge, verify, and explain AI-assisted knowledge rather than accept it passively (Elsayed, 2024; Forsler et al., 2026).

AI literacy has therefore emerged as a key concept in recent research. Early frameworks defined AI literacy broadly, combining technical understanding, ethical awareness, and general familiarity with AI systems (Chiu et al., 2024; Ng et al., 2021). More recent work highlights critical AI literacy, which emphasizes verification, bias awareness, ethical judgment, and reflective evaluation of AI outputs (Kong et al., 2023; Veldhuis et al., 2025). However, critical AI literacy is often treated as a static individual trait, with limited empirical attention to how it develops through interactions with AI systems.

Parallel to this, a growing body of research has identified prompt literacy as an emerging academic skill. Prompt literacy refers to students' ability to articulate goals, provide context, refine prompts iteratively, and request explanations from AI systems (Federiakin et al., 2024; Hwang et al., 2023; Lee & Palmer, 2025). Studies have shown that prompt quality significantly influences the relevance, clarity, and interpretability of AI responses (Kim et al., 2026; Knoth et al., 2024). Yet, prompt literacy has rarely been theorized as an antecedent that shapes students' critical evaluation and epistemic responsibility.

Another underexplored concept is epistemic transparency. Existing discussions of academic integrity largely emphasize compliance and detection (Bretag et al., 2019; Shishavan, 2024). In contrast, epistemic transparency focuses on students' ability to explain their reasoning, distinguish their own contributions from AI assistance, disclose AI use, and take responsibility for the accuracy of AI-assisted work (Bretag, 2018; Fricker, 2017; Rachha & Seyam, 2023). Treating transparency as an epistemic capability rather than a procedural rule offers a more meaningful approach to responsible AI-supported learning.

Beyond individual competencies, assessment design plays a critical institutional role in shaping AI use. Assessment structures signal what forms of knowledge, reasoning, and accountability are valued (Boud & Soler, 2016; Fischer et al., 2024). Research increasingly argues that assessments emphasizing explanation, reasoning, reflection, and disclosure can promote responsible AI engagement more effectively than surveillance-based approaches (Nikolopoulou, 2025; Xia et al., 2024).

Addressing these gaps, this study proposes and empirically tests an integrated framework linking prompt literacy, critical AI literacy, assessment design, and epistemic transparency in higher education. The study contributes by distinguishing interactional competence with AI from critical evaluative capacity, conceptualizing epistemic transparency as a distinct and measurable learning outcome, demonstrating the mediating role of critical AI literacy between prompt literacy and transparency, and highlighting assessment design as a key institutional driver of epistemically responsible AI use.

The subsequent parts of the paper are structured as follows. The next section reviews the relevant literature and develops the conceptual framework and hypotheses. This is followed by the methodology section outlining the research design, data collection, and analysis procedures. The results section presents the empirical findings, which are then discussed in relation to theory and prior research. The paper concludes with implications, limitations, and directions for future research.

2 Literature Review

2.1 | GenAI in Higher Education: Opportunities and Tensions

The rapid diffusion of GenAI has fundamentally reshaped teaching, learning, and assessment practices in higher education. Since 2022, a rapidly expanding body of empirical and review-based research has examined students' adoption of GenAI tools, their perceived usefulness, and the pedagogical opportunities associated with automated feedback, academic writing support, and problem-solving assistance (Abdallah et al., 2025; Baig & Yadegaridehkordi, 2024; Dempere et al., 2023). Meta-analytic and large-scale survey studies suggest that GenAI can enhance learning efficiency and conceptual understanding in certain contexts, particularly when used as a feedback mechanism (Wang & Fan, 2025).

However, beyond these benefits, scholars have consistently highlighted profound challenges related to academic integrity, overreliance, epistemic opacity, and the erosion of student accountability (Hackl et al., 2026; Johnston et al., 2024). Systematic reviews demonstrate that students frequently use GenAI in ways that blur the boundary between assistance and substitution, often without clear disclosure or understanding of ethical implications (Gruenhagen et al., 2024; Olohunfunmi & Khairuddin, 2024). As a result, the GenAI literature increasingly acknowledges that the central issue is no longer whether students use AI but rather how they use

it and how responsibility for AI-assisted knowledge is constructed.

Despite this growing attention, much of the literature remains instrumental and outcome oriented, focusing on performance gains, acceptance models, or integrity violations. Comparatively little research has examined the epistemic processes through which students interact with AI systems, evaluate AI-generated outputs, and ultimately assume responsibility for AI-assisted academic work, particularly within formal assessment contexts (Forsler et al., 2026; Mutanga et al., 2025).

2.2 | AI Literacy and Emergence of Critical AI Literacy

AI literacy has emerged as a foundational concept in the GenAI-in-education literature. Early frameworks conceptualized AI literacy as a combination of technical understanding, basic awareness of AI capabilities, and familiarity with ethical concerns (Chiu et al., 2024; Kong et al., 2023). However, more recent studies argue that such broad definitions insufficiently capture the cognitive and epistemic demands placed on learners using generative systems (Borge et al., 2024).

In response, scholars have advanced the notion of critical AI literacy, emphasizing students' abilities to verify AI-generated information, recognize bias and hallucinations, understand system limitations, and apply ethical judgment when integrating AI outputs into academic work (Elsayed, 2024; Hackl et al., 2026; Veldhuis et al., 2025). Empirical evidence suggests that students with higher levels of critical AI awareness are less likely to accept AI outputs uncritically and more likely to verify information against authoritative sources (Anderson & Bauml, 2026).

Nevertheless, the literature has largely treated critical AI literacy as a static individual attribute, often measured through self-reported awareness or ethical sensitivity. What remains underexplored is how such critical capacity develops through interaction with AI systems, and whether certain forms of engagement with GenAI foster or hinder evaluative judgment. This gap is particularly salient given evidence that many students possess surface-level awareness of AI risks but continue to rely heavily on AI outputs in assessed tasks (Kasneci et al., 2023; Long & Magerko, 2020; Ng et al., 2021).

2.3 | Prompt Literacy as Interactional Competence with GenAI

Parallel to studies on AI literacy, a growing body of research has focused on prompt engineering and literacy as new forms of interactional competence. Prompt literacy refers to learners' ability to articulate goals,

provide contextual information, iteratively refine prompts, and request explanations or alternative perspectives from AI systems (Federiakin et al., 2024; Knoth et al., 2024; Lee & Palmer, 2025). Studies have demonstrated that prompt quality significantly affects the relevance, accuracy, and explanatory depth of AI-generated responses (Knoth et al., 2024; Wang et al., 2025).

Recent pedagogical research argues that prompt literacy should be treated as a teachable academic skill rather than an intuitive or incidental capability (Federiakin et al., 2024). Students who actively refine prompts and interrogate AI reasoning appear more aware of AI limitations and uncertainties, suggesting a potential developmental link between interactional competence and critical evaluation (Aruleba et al., 2025; Hwang et al., 2023).

However, despite its growing prominence, prompt literacy has rarely been theorized as a distinct antecedent of critical AI literacy. Most studies examine prompting as a technical skill or instructional strategy without empirically modeling its role in shaping students' epistemic judgment or ethical responsibility. This represents a critical conceptual gap, as effective prompting may be a necessary condition for meaningful critical engagement with AI outputs.

2.4 | Epistemic Transparency and Responsibility

While AI literacy and integrity have been widely discussed, epistemic transparency remains undertheorized and undermeasured in higher education research. Epistemic transparency extends beyond ethical awareness to encompass students' willingness and ability to explain their reasoning, distinguish personal contributions from AI assistance, disclose AI use, and assume responsibility for the accuracy of AI-assisted work (Almassaad et al., 2024; Qu et al., 2025).

The concept draws on theories of epistemic agency and responsibility, which emphasize learners' obligations to justify knowledge claims and take ownership of epistemic outcomes (Hagège, 2023; Nieminen & Ketonen, 2024). From this perspective, the core concern is not merely whether AI is used ethically but whether learners remain accountable epistemic agents in AI-mediated knowledge production.

Existing studies on academic integrity have largely focused on compliance, detection, and policy enforcement (Bretag et al., 2019; Tight, 2024). In contrast, recent theoretical work argues for reframing integrity as an epistemic stance rather than a procedural rule, highlighting the importance of transparency, explainability, and accountability in student learning (Baldino & Balnaves, 2025). Empirical research examining these epistemic dimensions in the context of GenAI

remains scarce, creating a clear need for conceptual and measurement innovation.

2.5 | Assessment Design as an Institutional Driver of Responsible AI Use

Beyond individual competencies, scholars increasingly emphasize the role of assessment design in shaping how students engage with GenAI. Drawing on constructive alignment and authentic assessment theory, assessment is understood as a powerful signaling mechanism that communicates what forms of knowledge, reasoning, and accountability are valued within an institution (Barua & Lockee, 2025; Fischer et al., 2024).

Recent studies and policy reports have argued that traditional take-home and text-based assessments are particularly vulnerable to uncritical AI use, whereas assessments emphasizing reasoning, oral defense, reflection, and disclosure can promote responsible engagement with AI tools (Deep et al., 2025; Ncube et al., 2026). Sector-level guidance from quality assurance bodies similarly advocates assessment redesign rather than reliance on AI detection technologies (Nikolopoulou, 2025; Xia et al., 2024).

Despite this consensus, empirical research integrating assessment design with individual AI literacies remains limited. Most studies examine assessment strategies descriptively or normatively without modeling how assessment structures interact with students' prompt literacy or critical AI literacy to shape epistemically accountable outcomes.

2.6 | Distinguishing Epistemic Transparency from Related Constructs

Epistemic transparency is best understood as a practice and normative expectation that makes knowledge-producing processes, including human reasoning and human–AI interactions, visible, interpretable, and verifiable to relevant audiences. It emphasizes the disclosure of provenance, the articulation of reasoning steps, and the communication of uncertainty and model limitations so that others can evaluate the epistemic warrant of claims (Lloyd, 2025). This concept aligns with social epistemology's concern for how practices and institutions produce warranted beliefs, but it is specifically directed at making epistemic processes traceable and assessable in contexts where AI mediates knowledge production (Fricker, 2007; Goldman, 1999; Lloyd, 2025).

By contrast, academic integrity is primarily a normative and ethical framework governing honesty and fairness in scholarly conduct. It addresses plagiarism, fabrication, and misrepresentation and is enforced through policies and sanctions. While disclosure of AI

use can be an integrity practice, the aim of academic integrity is to uphold the norms of scholarship, such as authorship, credit, and originality rather than to explicate the cognitive or procedural mechanisms through which knowledge claims are produced (Harrad et al., 2024).

Metacognition refers to an individual's awareness and regulation of their own cognitive processes, such as planning, monitoring, and regulation. It is an intrapersonal cognitive skill that supports learning and self-assessment. When students reflect on how they use an AI tool, they exercise metacognitive control; however, metacognition does not, by itself, require institutional disclosure or standards for third-party appraisal (Flavell, 1979; Schraw & Moshman, 1995).

Epistemic agency denotes learners' ability to participate as knowers to ask questions, set epistemic goals, select methods, and take responsibility for knowledge claims. It emphasizes empowerment and participatory control over knowledge practices and links closely to assessment practices that cultivate evaluative judgment (students' ability to judge quality). Epistemic agency is therefore more agent centered and action-oriented than epistemic transparency, which focuses on what is made visible about processes rather than on who is empowered to act (Niemininen & Ketonen, 2024).

Finally, scholarship on evaluative judgment and AI-era assessment clarifies how these constructs interact. Assessment designs that require the documentation of AI use, justification of choices, and critical appraisal foster metacognition and epistemic agency while operationalizing epistemic transparency as an institutional expectation (Bearman et al., 2024).

2.7 | Research Gap and Need for the Present Study

Synthesizing the above literature reveals three critical gaps. First, existing GenAI research remains largely outcome focused and lacks process-oriented models explaining how students move from AI interaction to epistemic responsibility. Second, while AI literacy and critical AI literacy are well established, prompt literacy has not been sufficiently theorized as an antecedent shaping evaluative judgment. Third, the epistemic outcome of AI use—epistemic transparency—has not been empirically modeled, particularly in relation to assessment design. Addressing these gaps requires an integrative framework that connects interactional competence (prompt literacy), evaluative capacity (critical AI literacy), and institutional cues (assessment design) to explain epistemic transparency as a distinct and measurable learning outcome. The present study responds directly to this need by proposing and empirically testing a process-oriented conceptual framework that advances the understanding of responsible, accountable AI-assisted learning in higher education.

3 Conceptual Framework and Hypotheses Development

3.1 | Epistemic Transparency and Responsibility in AI-Supported Higher Education

The rapid integration of GenAI tools in higher education has raised important epistemological questions pertaining to how knowledge is created, validated, and disseminated in AI-supported teaching–learning environments. Within social epistemology, epistemic responsibility refers to the responsibility of individuals to critically assess and evaluate sources of knowledge, justify beliefs, and ensure the reliability and transparency of information adopted in decision-making and scholarly activities. When AI systems generate content or assist in academic activities, these responsibilities extend to how users understand, interpret, verify, and disclose AI-generated outputs (Lloyd, 2025). Consequently, the concept of epistemic transparency has emerged as a crucial principle for ensuring responsible human–AI collaboration in education and research.

Epistemic transparency involves making explicit the processes, assumptions, and limitations underlying knowledge production, particularly when AI systems contribute to academic outputs. Recent studies highlight that transparency in AI-supported learning encompasses acknowledging AI assistance, documenting prompt interactions, and critically evaluating the reliability of generated content (Walter, 2024). Such practices enable learners to maintain intellectual accountability while benefiting from AI-enhanced knowledge production. More importantly, epistemic transparency is not only a technological issue but also a pedagogical one that requires cultivating appropriate cognitive and evaluative competencies among learners to make them more ethically competent in using such technologies.

In this context, two competencies have gained increasing attention: prompt literacy and critical AI literacy. Prompt literacy refers to the ability of users of GenAI tools to effectively design, refine, and evaluate prompts when interacting with LLMs, thereby influencing the quality and reliability of AI-generated responses (Tolzin et al., 2024). However, critical AI literacy extends beyond operational skills and involves understanding the limitations, biases, and epistemic boundaries of AI systems (Walter, 2024). Together, these competencies enable learners to engage with AI outputs in a reflective and responsible manner to ensure ethics and integrity in the teaching–learning process.

Assessment design also plays a pivotal role in developing epistemic responsibility. Contemporary

assessment scholarship emphasizes the development of evaluative judgment, defined as the capability of students to critically appraise the quality and credibility of information and academic work (Bearman et al., 2024). In AI-supported learning environments, assessment practices that require students to justify their reasoning, document AI usage, and critically evaluate generated outputs can promote responsible engagement with AI tools. Thus, integrating prompt literacy, critical AI literacy, and assessment strategies that foster evaluative judgment can strengthen epistemic transparency and support responsible knowledge practices in higher education.

Further, the rapid integration of GenAI tools into higher education has fundamentally altered how students construct, justify, and take responsibility for knowledge. Although prior research has examined AI literacy and ethical AI use, how interactional competence with AI translates into epistemically transparent learning outcomes has received limited empirical attention, particularly within formal assessment environments (Barua & Lockee, 2025; Deep et al., 2025; Fischer et al., 2024; Ncube et al., 2026).

To address this gap, this study proposes a process-oriented conceptual framework that explains epistemic transparency as an emergent outcome shaped by individual competencies and institutional assessment design. The framework integrates four core constructs: prompt literacy, critical AI literacy, assessment design, and epistemic transparency (Figure 1).

3.2 | Background of the Framework

Prompt literacy represents students' capability to interact purposefully, contextually, and ethically with GenAI systems for their academic purposes.

Critical AI literacy reflects students' ability to evaluate, verify, and critically interrogate AI-generated outputs to ensure the ethical usage of AI for academic purposes.

Assessment design captures institutional signals embedded in assessment formats that emphasize reasoning, disclosure, and responsible AI use for academic evaluation purposes.

Epistemic transparency denotes students' ownership of, accountability for, and ability to explain their AI-assisted academic work. In the present study, epistemic transparency is conceptualized as the focal learning outcome for examining responsible AI-supported learning in higher education.

3.3 | Hypotheses Development

3.3.1 Prompt Literacy and Critical AI Literacy

Prompt literacy reflects students' ability to articulate learning goals, provide contextual inputs, iteratively

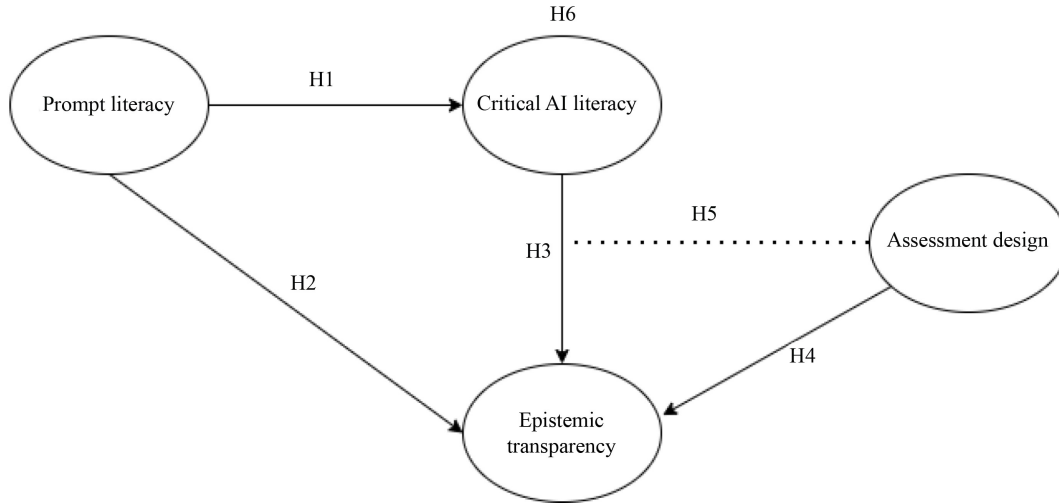


Figure 1 Conceptual framework underpinning this study. H1: Prompt literacy has a positive effect on critical AI literacy. H2: Prompt literacy has a positive effect on epistemic transparency. H3: Critical AI literacy has a positive effect on epistemic transparency. H4: Assessment design has a positive effect on epistemic transparency. H5: Critical AI literacy positively moderates the relationship between assessment design and epistemic transparency. H6: Critical AI literacy mediates the relationship between prompt literacy and epistemic transparency.

refine prompts, and request explanations from AI systems. Such interactional competence exposes learners to the limitations, variability, and uncertainty of AI-generated responses, encouraging reflective engagement rather than passive acceptance (Kim et al., 2026; Shibani et al., 2024).

From a learning theory perspective, meaningful interaction with AI systems fosters metacognitive awareness and evaluative judgment (Gonsalves, 2026), which are foundational to critical AI literacy. Students who actively refine prompts and interrogate AI reasoning are more likely to recognize biases, hallucinations, and contextual mismatches in AI outputs (Walker et al., 2025). Hence, it is hypothesized that:

H1: *Prompt literacy has a positive effect on critical AI literacy.*

3.3.2 Prompt Literacy and Epistemic Transparency

Epistemic transparency refers to students' capacity to explain their reasoning, distinguish personal contributions from AI assistance, and assume responsibility for AI-supported academic work (Kim et al., 2026). Prompt literacy contributes to this outcome by encouraging intentional engagement with AI rather than reliance on opaque outputs (Favero, 2024).

However, prompt competence alone may not fully ensure epistemic accountability, as students may still accept AI outputs uncritically despite well-framed prompts (Park & Choo, 2025). Accordingly, the direct influence of prompt literacy on epistemic transparency is expected to be positive. Hence, it is hypothesized that:

H2: *Prompt literacy has a positive effect on epistemic transparency.*

3.3.3 Critical AI Literacy and Epistemic Transparency

Critical AI literacy plays a central epistemic role in AI-assisted learning environments. Students who verify AI-generated information, recognize biases, and understand AI limitations are better positioned to maintain epistemic ownership of their academic work (Chai et al., 2024; Rad et al., 2024).

From an epistemic agency perspective, such critical engagement enables learners to justify knowledge claims, disclose AI use transparently, and defend AI-assisted outputs in evaluative settings. Thus, critical AI literacy is expected to be a strong predictor of epistemic transparency.

H3: *Critical AI literacy has a positive effect on epistemic transparency.*

3.3.4 Assessment Design and Epistemic Transparency

Assessment design constitutes a powerful institutional mechanism that shapes student behavior. Assessments that emphasize explanation of reasoning, oral or viva-based evaluation, and transparent AI use guidelines signal that process matters as much as outcomes (Tang et al., 2024).

These design features compel students to articulate their reasoning, disclose AI assistance, and assume responsibility for submitted work, thereby directly fostering epistemic transparency (Barelli et al., 2025; Cheng et al., 2024; Gerdes, 2022). Importantly, these effects may operate independently of individual AI skills.

H4: *Assessment design has a positive effect on epistemic transparency.*

3.3.5 Moderating Role of Critical AI Literacy

It is theoretically plausible that students with higher critical AI literacy respond more effectively to transparent assessment designs because they possess a greater evaluative capacity to align AI use with epistemic expectations (Russo et al., 2024). Accordingly, critical AI literacy is hypothesized to strengthen the relationship between assessment design and epistemic transparency.

H5: Critical AI literacy positively moderates the relationship between assessment design and epistemic transparency.

3.3.6 Mediating Role of Critical AI Literacy

This study conceptualizes critical AI literacy as a core mediating mechanism linking prompt literacy to epistemic transparency. Prompt literacy equips students with interactional competence (Federiakin et al., 2024), but it is through critical AI literacy that such competence is transformed into epistemic responsibility and transparent learning outcomes.

This mediation logic aligns with process-based models of learning, in which interactional skills lead to evaluative judgment, which in turn enables accountable knowledge construction.

H6: Critical AI literacy mediates the relationship between prompt literacy and epistemic transparency.

4 Methodology

4.1 | Research Design

This study used a quantitative, cross-sectional survey design to examine the relationships among prompt literacy, critical AI literacy, assessment design, and epistemic transparency in GenAI use in higher education. A cross-sectional approach was appropriate, as the objective was to capture students' competencies, perceptions, and learning accountability in AI-mediated environments (Kesmodel, 2018). The study is explanatory and predictive, aiming to test theoretically grounded hypotheses and assess the practical relevance of the proposed model.

4.2 | Instrument Development and Validation

4.2.1 Item Generation and Theoretical Grounding

The questionnaire was developed using a systematic, multistage instrument development process to ensure theoretical rigor and measurement validity. First, an

extensive review of contemporary literature on AI literacy, prompt engineering, critical digital literacy, epistemic agency, academic integrity, and assessment design was conducted. Measurement items for prompt literacy, critical AI literacy, and assessment design were adapted from well-established conceptual and empirical studies, such as Ng et al. (2024), while ensuring contextual alignment with AI-supported learning.

Epistemic transparency, which represents the central theoretical contribution of this study, was developed as a new construct to capture students' epistemic responsibility in, accountability for, and ability to explain AI-assisted academic work. Its items were grounded in epistemic agency theory, academic integrity scholarship, and explainable AI literature.

4.2.2 Focus Group and Expert Validation

To enhance content relevance and contextual clarity, a focus group discussion was conducted with higher education faculty members and postgraduate students experienced in using GenAI tools (Módné Takács et al., 2023). This qualitative step helped refine construct boundaries, improve item phrasing, and ensure that the instrument reflected authentic academic practices rather than abstract technological usage.

Subsequently, the revised questionnaire was evaluated by a panel of three academic experts to establish content and face validity (Patel & Desai, 2020). The experts assessed each item for clarity, relevance, and representativeness. Minor modifications were incorporated based on their feedback to enhance precision and readability without altering the conceptual intent.

4.2.3 Pilot Testing

A pilot study was conducted with 46 students to evaluate the clarity, readability, and preliminary reliability of the research instrument before administering the main survey. The pilot participants were recruited independently and were not included in the final study sample. Construct-wise reliability analysis demonstrated acceptable internal consistency across all four constructs, with Cronbach's alpha values of 0.797 for prompt literacy, 0.784 for critical AI literacy, 0.781 for assessment design, and 0.873 for epistemic transparency. Based on the reliability assessment and participant feedback, no questionnaire items were removed; only minor wording revisions were made to improve the clarity and readability of a few statements, while the underlying constructs, measurement structure, and number of items remained unchanged. The revised instrument was subsequently administered for the main survey.

4.3 | Data Collection Procedure

Data were collected between December 3, 2025 and January 1, 2026 using an online questionnaire administered through the Qualtrics survey platform. A convenience sampling approach was adopted. The survey link was initially circulated through faculty members' professional academic networks in the Mysuru and Mangaluru regions of Karnataka, India. Faculty members and departmental coordinators subsequently disseminated the questionnaire to undergraduate (UG) and postgraduate (PG) students within their respective higher education institutions through institutional communication channels and student social media groups. The invitation pool comprised students from commerce, management, accounting, finance, economics, and related disciplines who had prior exposure to GenAI tools for academic purposes. The research team conducted periodic follow-up communications with faculty members throughout the data collection period to encourage participation. Participation was voluntary, anonymous, and based on informed consent. All questionnaires were administered exclusively in English. Before the main survey, the instrument was reviewed through a focus group, expert evaluation, and pilot testing to ensure clarity, readability, and contextual appropriateness. Further details will be presented in the Electronic Supplementary Material.

A total of 726 responses were received through the Qualtrics survey platform. The dataset was subjected to a rigorous multi-stage screening process before statistical analysis. First, responses were screened for duplicate submissions, completeness, and data quality. Responses with less than 95% questionnaire completion were excluded to ensure adequate data quality and analytical reliability. Each remaining response was then examined for missing values, response consistency, and overall suitability for partial least square structural equation modeling (PLS-SEM) analysis. Consistent with recommended practices for behavior research, a 5% respondent-level missingness threshold was adopted (Newman, 2014). Cases satisfying the completion criterion but containing minimal item-level missing data were retained, and the remaining missing values were imputed using multivariate imputation by chained equations (MICE) with fully conditional specification over 10 iterations, thereby preserving the multivariate structure of the dataset (van Buuren & Groothuis-Oudshoorn, 2011). Imputed values were constrained within the original five-point Likert-scale response range to maintain the ordinal properties of the measurement scale (Wu et al., 2015). Following the predefined screening criteria, 77 responses were excluded because they failed to satisfy the minimum completion requirement and other predefined data-quality criteria, resulting in a final analytical sample of 649 valid questionnaires used for

subsequent analyses (see Table 1). All valid responses were included, as the final sample size exceeded the recommended minimum thresholds—that is, 300 samples for PLS-SEM analysis—and ensured strong statistical power (Hair et al., 2022). Participation was voluntary, informed consent was obtained electronically, and respondents were assured of anonymity and confidentiality. No personally identifiable information was collected.

4.4 | Demographic Profile of Respondents

The final sample consisted of 649 students (see Table 1). In terms of gender, 374 respondents (57.6%) were male and 275 respondents (42.4%) were female. Regarding age, the majority of respondents were below 25 years of age, with 46.4% below 20 years and 52.2% between 20 and 24 years. A smaller proportion of respondents belonged to older age categories.

With respect to level of study, 545 respondents (84.0%) were undergraduate students, while 104 respondents (16.0%) were postgraduate students.

The respondents represented a range of

Table 1 Demographic profile of respondents ($n = 649$)

Category	Type	<i>n</i>	Percentage (%)
Gender	Male	374	57.6
	Female	275	42.4
Age group	Below 20	301	46.4
	20–24	339	52.2
	25–29	4	0.6
	30 and above	5	0.8
Level of study	UG	545	84.0
	PG	104	16.0
Discipline	Commerce	160	24.7
	Accounting	4	0.6
	Management	344	53.0
	Economics	1	0.2
	Finance	18	2.8
	Other	122	18.8
Type of institution	Government	84	12.9
	Private	118	18.2
	Deemed or autonomous	447	68.9
Prior exposure to GenAI	Less than 6 months	263	40.5
	6–12 months	190	29.3
	1–2 years	120	18.5
	More than 2 years	76	11.7
Received formal training on AI use	Yes	122	18.8
	No	527	81.2

Notes. UG: undergraduate, PG: postgraduate.

academic disciplines. Management studies constituted the largest group (53.0%), followed by commerce, finance, accounting, economics, and other allied disciplines.

Regarding institutional affiliation, 68.9% of respondents were enrolled in deemed or autonomous institutions, 18.2% attended private institutions and 12.9% were from government institutions.

In terms of prior exposure to GenAI, 40.5% of respondents reported using GenAI for less than 6 months, while the remaining respondents reported longer periods of use, including 11.7% with more than two years of experience. Only 18.8% of respondents indicated that they had received formal training in the use of GenAI.

Table 2 depicts the outer loadings and measurement model. The outer loadings presented in the table indicate that all measurement items demonstrate

Table 2 Outer loadings and measurement model

Items	Outer loadings	CR	Cronbach's alpha	AVE	VIF
AD1	0.816				2.012
AD2	0.816				1.978
AD3	0.804				1.920
AD4	0.796				1.915
AD5	0.844	0.908	0.874	0.6650	2.243
CAIL1	0.791				1.877
CAIL2	0.752				1.703
CAIL3	0.758				1.741
CAIL4	0.795				1.887
CAIL5	0.756				1.676
CAIL6	0.698	0.891	0.852	0.5760	1.488
EPT1	0.788				2.039
EPT2	0.806				2.220
EPT3	0.776				2.001
EPT4	0.753				1.904
EPT5	0.761				1.862
EPT6	0.720				1.670
EPT7	0.726				1.792
EPT8	0.760	0.917	0.896	0.5810	1.946
PL1	0.689				1.586
PL2	0.718				1.695
PL3	0.716				1.607
PL4	0.662				1.399
PL5	0.745				1.640
PL6	0.682				1.548
PL7	0.732	0.875	0.833	0.4996	1.609

Notes. AD: assessment design, CAIL: critical AI literacy, EPT: epistemic transparency, PL: prompt literacy, CR: composite reliability, AVE: average variance extracted, VIF: variance inflation factor.

satisfactory individual item reliability, with values exceeding the recommended threshold of 0.60, confirming that each indicator adequately represents its corresponding construct (Hair et al., 2022). Composite reliability (CR) values for all constructs are above 0.70 (ranging from 0.875 to 0.917), indicating strong internal consistency reliability within each construct (Hair et al., 2022). Similarly, Cronbach's alpha values exceed the 0.70 benchmark, further supporting the reliability of the measurement scales (Brown, 2002). Average variance extracted (AVE) values range from 0.4996 to 0.665, with the prompt literacy construct showing an AVE of 0.4996, marginally below the conventional threshold of 0.50. This confirms convergent validity, meaning that the indicators share a high proportion of variance with their respective latent constructs (Fornell & Larcker, 1981). Variance inflation factor (VIF) values are all below the critical value of 5, ranging from 1.399 to 2.243. This indicates the absence of significant multicollinearity issues among the indicators, ensuring the stability and reliability of the measurement model (Hair et al., 2022). These results demonstrate strong internal consistency reliability and generally satisfactory measurement properties, although the marginally sub-threshold AVE for prompt literacy should be acknowledged as a measurement limitation. The high outer loadings, CR, Cronbach's alpha, and AVE values collectively affirm that the constructs are well measured and suitable for subsequent structural analysis. Further, the prompt literacy construct demonstrated satisfactory psychometric properties despite three indicators (PL1 = 0.689, PL4 = 0.662, and PL6 = 0.682) exhibiting outer loadings slightly below the commonly referenced guideline of 0.708. Contemporary PLS-SEM guidelines emphasize that reflective indicators with outer loadings between 0.40 and 0.70 should not be removed automatically; rather, decisions regarding indicator retention should consider construct reliability, convergent validity, theoretical relevance, and content validity (Hair et al., 2022). In the present study, the prompt literacy construct demonstrated satisfactory internal consistency (Cronbach's alpha = 0.833; CR = 0.875). Although the AVE (0.4996) was marginally below the conventional guideline of 0.50, it should be interpreted alongside the satisfactory reliability estimates and the theoretical contribution of the retained indicators rather than as an isolated decision criterion. Retaining PL1, PL4, and PL6 preserved the conceptual breadth of the prompt literacy construct while maintaining satisfactory construct reliability and acceptable convergent validity, consistent with recommended PLS-SEM measurement assessment and reporting practices (Hair et al., 2022; Hair et al., 2019).

4.5 | Discriminant Validity

Table 3 presents the heterotrait-monotrait (HTMT) ratios used to assess discriminant validity among the

Table 3 Heterotrait–monotrait ratio matrix for discriminant validity

Construct	Assessment design	Critical AI literacy	Epistemic transparency	Prompt literacy
Assessment design				
Critical AI literacy	0.782			
Epistemic transparency	0.918	0.873		
Prompt literacy	0.720	0.849	0.753	

Note. Values below 0.90 generally indicate adequate discriminant validity.

study constructs. Most HTMT values were below the conservative threshold of 0.90. However, the HTMT value between assessment design and epistemic transparency (HTMT = 0.918) marginally exceeded this heuristic guideline. Contemporary PLS-SEM literature recommends that HTMT should not be interpreted solely based on heuristic cut-off values but should also be evaluated using bootstrapped confidence intervals. In the present study, the 95% percentile confidence interval (0.872–0.956) and the bias-corrected confidence interval (0.868–0.954) for this construct pair remained entirely below the critical value of 1.00, indicating that discriminant validity was established despite the elevated HTMT value (Henseler et al., 2015). Furthermore, assessment design and epistemic transparency represent conceptually distinct constructs within the proposed theoretical framework, supporting their retention as separate reflective constructs. Therefore, the measurement model demonstrated acceptable discriminant validity, consistent with current PLS-SEM recommendations (Hair et al., 2022).

4.6 | Data Analysis Strategy

4.6.1 PLS-SEM Procedure

Data analysis was conducted using SmartPLS software. The PLS-SEM procedure followed a two-step approach involving assessment of the measurement model followed by evaluation of the structural model. Bootstrapping with 5,000 resamples was used to assess the significance of path coefficients, indirect effects, and the interaction effect. To examine whether critical AI literacy moderated the relationship between assessment design and epistemic transparency, an interaction term (assessment design $\times$ critical AI literacy) was constructed in SmartPLS and evaluated exclusively within the structural model (Hair et al., 2022). Because the interaction term represents a product term for moderation rather than a separately specified reflective latent construct, it was not included in the measurement-model assessment or in the HTMT matrix.

4.6.2 Predictive Assessment and IPMA

To enhance robustness, PLS-predict was employed to assess out-of-sample predictive relevance. Positive Q^2_{predict} values for both endogenous constructs confirmed strong predictive performance, with lower root mean square error (RMSE) and mean absolute error (MAE) values indicating accurate predictions. Additionally, importance–performance map analysis (IPMA) was conducted at the latent variable level to provide applied insights. The IPMA results showed comparable performance levels across constructs, with critical AI literacy exhibiting the highest performance score, underscoring its central role in improving epistemic transparency in AI-assisted learning.

4.7 | Methodological Robustness

The study used a non-probability online recruitment strategy and retained 649 complete responses after screening for quality and completeness. To increase methodological transparency and reduce inferential bias, the study implemented the following procedures:

(1) Procedural safeguards to reduce common method bias, including anonymous responses, neutral item phrasing, and required minimum completion time. Further, the study attempted to examine the possibility of common method bias. Harman’s single-factor test was conducted by entering all measurement items into an exploratory factor analysis using an unrotated principal component solution. The results revealed that multiple factors emerged and the first factor accounted for 45.133% of the total variance, which is below the recommended threshold of 50% (Podsakoff et al., 2003). This indicates that common method bias is unlikely to pose a serious threat to the validity of the study. In addition, all VIF values were below the recommended threshold of 3.3, further suggesting that common method bias was not a concern in the study (Kock, 2015).

(2) Data quality screening to remove inattentive responses, specifically the 95% completion criteria.

(3) Reporting of respondent demographics and prior AI exposure (Table 1) to enable the assessment of sample composition.

5 Results

The structural model results presented in Table 4 indicate that prompt literacy has a strong and statistically significant positive effect on critical AI literacy ($\beta = 0.718, p < 0.001$), suggesting that students with stronger prompt literacy are more likely to demonstrate higher levels of critical AI literacy. Prompt literacy also exerts a

Table 4 Structural path results

Hypotheses	Path coefficients	β	SD	<i>t</i> statistics	<i>p</i> values	2.5% CI LL	97.5% UL	Decision
H1	Prompt literacy → critical AI literacy	0.718	0.024	29.541	< 0.001	0.665	0.762	Supported
H2	Prompt literacy → epistemic transparency	0.074	0.035	2.087	0.037	0.003	0.140	Supported
H3	Critical AI literacy → epistemic transparency	0.356	0.045	7.935	< 0.001	0.268	0.445	Supported
H4	Assessment design → epistemic transparency	0.525	0.045	11.628	< 0.001	0.434	0.608	Supported
H5	Assessment design × critical AI literacy → epistemic transparency	0.029	0.019	1.588	0.112	−0.002	0.071	Not supported
H6	Prompt literacy → critical AI literacy → epistemic transparency	0.255	0.033	7.720	< 0.001	0.192	0.322	Supported (mediation)

Notes. β : standardized path coefficient, SD: standard deviation, CI: confidence interval, LL: lower limit, UL: upper limit.

positive but comparatively modest direct effect on epistemic transparency ($\beta = 0.074$, $p = 0.037$), indicating that prompt literacy contributes directly to epistemic transparency, although the magnitude of this effect is relatively small. Critical AI literacy has a significant positive effect on epistemic transparency ($\beta = 0.356$, $p < 0.001$), demonstrating that higher levels of critical AI literacy enhance students' epistemic transparency in AI-supported learning environments. Likewise, assessment design has a strong and statistically significant positive effect on epistemic transparency ($\beta = 0.525$, $p < 0.001$), highlighting the important role of well-designed assessments in fostering transparent and accountable learning. In contrast, the interaction effect between assessment design and critical AI literacy is not statistically significant ($\beta = 0.029$, $p = 0.112$), indicating that assessment design does not significantly moderate the relationship between critical AI literacy and epistemic transparency. Furthermore, the indirect effect of prompt literacy on epistemic transparency through critical AI literacy is positive and statistically significant ($\beta = 0.255$, $p < 0.001$), supporting the mediating role of critical AI literacy. The total effect of prompt literacy on epistemic transparency is also significant ($\beta = 0.329$, $p < 0.001$), indicating that prompt literacy influences epistemic transparency both directly and indirectly through critical AI literacy. Together, these findings provide evidence of partial mediation, as both the direct and indirect effects remain statistically significant.

The R^2 values (Table 5) indicate the proportion of variance in the dependent constructs explained by the model. Critical AI literacy has an R^2 of 0.516 (adjusted 0.515), meaning that approximately 51.6% of its variance is accounted for by the predictor variables, reflecting moderate to substantial explanatory power. Epistemic transparency shows a higher R^2 of 0.750 (adjusted 0.748), indicating that 75% of its variance is explained by the model, which represents strong explanatory power. These values demonstrate that the model effectively explains a significant portion of the variance in both constructs, with particularly strong predictive accuracy for epistemic transparency. The

close alignment between the R^2 and the adjusted R^2 values also suggests that the model is well specified without overfitting.

Table 5 Coefficient of determination (R^2) results

Construct	R^2	R^2 adjusted
Critical AI literacy	0.516	0.515
Epistemic transparency	0.750	0.748

Note. R^2 represents the proportion of variance explained in the endogenous construct by the predictor variables.

The f^2 values (Table 6) indicate the relative effect sizes of the predictors on the dependent variables in the model.

Table 6 Effect size (f^2) results

Structural path	f^2
Assessment design → epistemic transparency	0.559
Assessment design × critical AI literacy → epistemic transparency	0.006
Critical AI literacy → epistemic transparency	0.201
Prompt literacy → critical AI literacy	1.065
Prompt literacy → epistemic transparency	0.010

Notes. f^2 represents the effect size of exogenous constructs on endogenous constructs in the structural model. Values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively.

Assessment design → epistemic transparency (0.559): This shows a **large practical effect**, suggesting that how assessments are designed significantly influences epistemic transparency.

Assessment design × critical AI literacy → epistemic transparency (0.006): The interaction **practical effect is negligible**, indicating that the combined influence of assessment design and critical AI literacy on epistemic transparency is minimal.

Critical AI literacy → epistemic transparency (0.201): This reflects a **medium practical effect**, which means critical AI literacy alone contributes meaningfully to epistemic transparency.

Prompt literacy → critical AI literacy (1.065): A

large practical effect size, showing that prompt literacy strongly predicts critical AI literacy.

Prompt literacy $\rightarrow$ epistemic transparency (0.010): **It falls below the threshold for a small effect**, implying that prompt literacy has little direct impact on epistemic transparency.

Thus, the results show that prompt literacy primarily enhances epistemic transparency indirectly through its strong influence on critical AI literacy, while assessment design directly affects epistemic transparency with strong strength.

The Q^2_{predict} values in Table 7 indicate good predictive relevance for both constructs, with epistemic transparency (0.684) showing stronger predictive power than critical AI literacy (0.512). Lower RMSE and MAE values for epistemic transparency (0.564 and 0.417) compared with critical AI literacy (0.701 and 0.533) suggest that the model predicts epistemic transparency more accurately and with fewer errors (Sharma et al., 2021). Finally, these results demonstrate that the model performs well in predicting both critical AI literacy and epistemic transparency, with especially reliable predictions for epistemic transparency.

Table 7 PLS-predict results

Constructs	Q^2_{predict}	RMSE	MAE
Critical AI literacy	0.512	0.701	0.533
Epistemic transparency	0.684	0.564	0.417

Notes. Q^2_{predict} values greater than zero indicate the predictive relevance of the PLS-SEM model. RMSE: root mean square error, MAE: mean absolute error.

The IPMA results in Table 8 show that all constructs have similar performance levels, with critical AI literacy scoring the highest at 67.344, closely followed by epistemic transparency at 66.840, assessment design at 66.127, and prompt literacy at 65.742. This indicates that critical AI literacy is currently the strongest performer among the factors, suggesting that it may be the most influential area to focus on for improving overall outcomes. The relatively close scores imply balanced contributions from all constructs, but prioritizing critical AI literacy could yield the most impact based on its slightly higher performance.

Table 8 Importance–performance map analysis results

Construct	Performance level
Assessment design	66.127
Critical AI literacy	67.344
Epistemic transparency	66.840
Prompt literacy	65.742

Note. The latent variable performance scores indicate the average performance level of each construct in the structural model.

6 Discussion

The findings of this study provide a detailed understanding of the relationships among prompt literacy, critical AI literacy, assessment design, and epistemic transparency. Notably, prompt literacy emerges as a fundamental factor with a very strong positive influence on critical AI literacy, as demonstrated by the high path coefficient ($\beta = 0.718$, $p < 0.001$). This significant effect highlights the critical role that the ability to craft effective prompts plays in enabling students to engage deeply and critically with AI systems. Such engagement is essential for navigating the complexities of AI outputs, which often require sophisticated interpretive skills to assess their validity and relevance. This result aligns with contemporary perspectives emphasizing user competence as a cornerstone for meaningful human–AI interaction, suggesting that enhancing prompt literacy could be a strategic focus for educational programs aimed at fostering critical AI engagement (Chiu et al., 2024; Kong et al., 2023).

In addition to its impact on critical AI literacy, prompt literacy also demonstrates a statistically significant but modest direct effect on epistemic transparency ($\beta = 0.074$, $p = 0.037$). This indicates that proficiency in prompt formulation not only equips users with the skills to critically evaluate AI-generated information but also makes a modest direct contribution to clearer and more transparent knowledge representation. This direct relationship suggests that prompt literacy influences how knowledge is accessed and understood, potentially by enabling users to elicit more precise, relevant, and interpretable AI responses. Therefore, prompt literacy serves a dual function by substantially strengthening critical AI literacy while also making a modest direct contribution to epistemic transparency.

Critical AI literacy itself is shown to have a moderate positive effect on epistemic transparency ($\beta = 0.356$, $p < 0.001$), reinforcing the idea that the capacity to critically analyze AI outputs is pivotal for understanding the epistemic foundations of AI-generated knowledge. This finding highlights the importance of cultivating critical AI literacy as a means of promoting transparency, as users with higher critical literacy are better positioned to discern the reliability, biases, and limitations of AI systems. Consequently, critical AI literacy acts as a key mediator in enabling users to interpret AI outputs from a more informed and reflective perspective, which is crucial for responsible AI use. Furthermore, it allows students to retain and enhance their critical thinking throughout their learning process.

Assessment design also plays a significant role, exhibiting a strong positive effect on epistemic transparency ($\beta = 0.525$, $p < 0.001$). This finding emphasizes

the importance of well-structured, thoughtfully designed assessments in fostering an environment in which transparent and comprehensive knowledge communication can occur. The strength of this effect suggests that assessment design is a critical lever for educators and instructional designers to enhance epistemic transparency independent of users' individual literacy levels. By creating assessments that clearly articulate expectations, criteria, and feedback mechanisms, educators can help learners develop a clearer understanding of AI-related content and processes (Barua & Locke, 2025; Fischer et al., 2024). This allows educators to differentiate students performance within AI-supported learning environment and establish robust evaluation criteria that directly enhance the transparency and accountability of the assessment process.

Interestingly, the interaction effect between assessment design and critical AI literacy on epistemic transparency is not statistically significant ($\beta = 0.029$, $p = 0.112$), indicating that these variables contribute independently rather than synergistically. This suggests that improvements in assessment design can enhance epistemic transparency regardless of the learner's level of critical AI literacy, and vice versa. Such independence implies that interventions targeting either factor can be effective in isolation, offering flexibility in educational strategies aimed at improving transparency.

Finally, the mediation analysis revealed a significant indirect effect of prompt literacy on epistemic transparency through critical AI literacy ($\beta = 0.255$, $p < 0.001$). The direct effect ($\beta = 0.074$, $p = 0.037$) and the total effect ($\beta = 0.329$, $p < 0.001$; 95% BCa CI [0.249, 0.406]) were also statistically significant, indicating partial mediation. These findings suggest that prompt literacy influences epistemic transparency through both a direct pathway and an indirect pathway via critical AI literacy, supporting the proposed theoretical framework. The significance of both the direct and indirect effects indicates partial rather than full mediation, suggesting that prompt literacy influences epistemic transparency both independently and through the development of critical AI literacy.

While the results show robust associations among prompt literacy, critical AI literacy, and epistemic transparency, the various additional arguments enhance the merit of the discussion. First, self-reported prompt literacy may partly capture students' confidence with technology, familiarity with AI tools, or a general propensity to report competence (social desirability). That is, students who say they are good at prompting may also be more comfortable with digital tools or more willing to report ethical awareness characteristics that can correlate with critical AI literacy and epistemic transparency without necessarily reflecting pure technical prompt-crafting skills. Therefore, the study interprets the strong association between prompt

literacy and critical AI literacy as evidence of a substantive relationship while acknowledging that it may be conflated with confidence and exposure effects. Second, reverse or reciprocal relationships are plausible. For example, rather than prompt skill unidirectionally leading to transparency, students with higher epistemic transparency—a disposition to disclose and justify AI use—may be more likely to perceive assessments as clear and to engage more actively with prompts.

Similarly, a clearer assessment design could shape students' reported critical literacy by signaling expectations and encouraging reflective behavior. Because the current cross-sectional design captures associations at a single point in time, the study cannot fully adjudicate between these temporal explanations. It therefore describes the findings as associations or predictive links rather than causal effects and recommends longitudinal or experimental studies. Third, measurement and method factors might partially inflate associations. Although procedural remedies, Harman's single-factor test (first factor = 45.13%), and full-collinearity VIF diagnostics did not indicate dominant common method bias, residual social desirability or response tendencies may still influence self-reports. In short, while the theoretical interpretation that prompt literacy enables critical engagement with AI is plausible and consistent with prior literature, readers of this study should treat the findings as one piece of evidence that requires complementary experimental and qualitative work to confirm causal mechanisms.

Practically, these alternative interpretations do not nullify the educational implications but do change their emphasis. If prompt literacy partly reflects exposure/confidence, interventions should combine technical prompt training with measures that increase equitable access and reduce confidence gaps (for example, scaffolded practice, peer support, and institutional AI training). If the relationship is bidirectional, then assessment reforms that promote explicit disclosure and reasoning could themselves foster both prompt and critical literacies. Thus, an integrated approach combining skill training, supportive assessment design, and institutional policy remains appropriate, while further research clarifies causal paths.

These results contribute valuable insights into the relationship between user competencies and instructional design in AI-mediated contexts. They suggest that educational initiatives should adopt a multifaceted approach that simultaneously develops prompt literacy and critical AI literacy while also optimizing assessment design. Such a comprehensive strategy is likely to maximize epistemic transparency, thereby promoting more informed, critical, and transparent interactions with AI technologies. Future research could further explore how these factors operate across diverse populations and AI applications, as

well as investigate additional moderating variables that might influence these relationships.

6.1 | Theoretical Contribution

This study advances AI-in-education theory by distinguishing interactional AI competence from critical evaluative capacity, two dimensions often conflated within AI literacy. By conceptualizing prompt literacy as interactional competence, the framework emphasizes students' ability to orchestrate interactions with GenAI through goal articulation, contextualization, and iterative refinement. This aligns with views of AI as a co-intelligent partner requiring human direction (Mima, 2025; Mollick & Mollick, 2023). Critical AI literacy is theorized as an evaluative capability encompassing verification, bias awareness, and ethical judgment, drawing on critical digital literacy traditions (Mikeladze et al., 2024; Rastogi, 2024; Selwyn, 2016). The study refines AI literacy theory by positioning interactional competence as an antecedent to evaluative judgment, introducing a distinction between using AI effectively and evaluating it responsibly.

Second, the study makes a novel epistemic contribution by positioning epistemic transparency as a distinct epistemic outcome rather than an automatic consequence of AI literacy. Research often assumes that awareness of AI limitations translates into responsible academic practice. However, this framework shows that epistemic transparency requires additional normative commitments, including ownership of reasoning and willingness to disclose AI assistance in academic work. This conceptualization builds on theories of epistemic agency and responsibility, which emphasize learners' obligations to justify knowledge claims (Bretag, 2018; Fricker, 2017; Kalasampath et al., 2025; Rachha & Seyam, 2023). By separating critical AI literacy from epistemic transparency, this study extends debates on academic integrity beyond procedural compliance, aligning with perspectives that frame integrity as an epistemic stance. Accordingly, epistemic transparency is theorized as a measurable capability essential for credible knowledge production in AI-mediated learning.

The framework demonstrates the primacy of assessment design as an institutional driver of epistemically responsible AI use, shifting the focus from individual competencies to structural conditions that shape learning behavior. Drawing on assessment theory, assessment acts as a signaling mechanism that communicates valued forms of knowledge and accountability in educational systems (Boud & Soler, 2016). The influence of assessment design on epistemic transparency shows that reasoning-oriented tasks and explicit AI guidelines compel epistemic accountability, often independently of students' critical AI literacy. This aligns

with policy discussions advocating assessment reform over surveillance for GenAI (Boud & Soler, 2016; Shishavan, 2024). These insights advance a systems-level perspective, positioning responsible AI use as an achievement shaped by learner capabilities and assessment design.

6.2 | Limitations and Future Research

Despite the study's contributions, it has two methodological limitations that should be considered when interpreting the findings. First, the cross-sectional design captures associations at a single point in time and therefore does not permit strong causal inference. Consequently, the study avoids causal wording and interprets results as associations or predictive relationships; longitudinal or experimental designs are required to establish temporal precedence and causality. Second, the sample was recruited online using convenience methods, which may introduce self-selection and coverage bias: participants who opted into the survey may differ systematically from non-respondents in motivation, AI familiarity, or access to digital resources. Although the final sample ($n = 649$) exceeds the recommended thresholds for PLS-SEM and includes diversity across disciplines and institution types, generalizability beyond similar student populations is limited.

To strengthen causal inference and external validity, future research should adopt longitudinal panel designs or randomized controlled trials that manipulate instructional interventions (e.g., prompt engineering training, critical AI literacy modules) and track changes in epistemic transparency over time. Broader probability-based sampling or stratified, multi-site recruitment, particularly including under-resourced and rural institutions, would improve generalizability. Finally, mixed-methods approaches (qualitative interviews and think-aloud protocols) can uncover the cognitive and contextual mechanisms behind the associations observed in the study.

7 Conclusions

This study examined how students engage with GenAI in higher education and what helps them remain responsible when using AI academically. By focusing on prompt literacy, critical AI literacy, assessment design, and epistemic transparency, the study shows how skills and practices shape AI-supported learning. The findings reveal prompt literacy as foundational. Students who frame clear, purposeful prompts develop stronger critical AI literacy, helping them question AI outputs and avoid uncritical reliance on AI outputs. Prompt literacy also makes a modest direct contribution to epistemic transparency by helping students obtain

clearer AI responses; however, its strongest influence operates through the development of critical AI literacy. Critical AI literacy is central to this process. Students who verify AI information, reflect on bias, and consider ethics are better at explaining their reasoning and being open about AI use. The study confirms that critical AI literacy partially mediates the relationship between prompt literacy and epistemic transparency, highlighting both direct and indirect pathways through which prompt literacy supports responsible AI use.

Assessment design is a key institutional factor. Assessments emphasizing explanation, reasoning, and disclosure improve epistemic transparency, regardless of students' AI literacy. This shows that responsibility in AI use requires institutional support. Assessment design and critical AI literacy make independent contributions to epistemic transparency, indicating that improvements in assessment practices can enhance transparent AI-supported learning regardless of students' critical AI literacy. The results indicate that fostering responsible AI-supported learning requires the simultaneous development of prompt literacy and critical AI literacy, supported by assessment practices that emphasize reasoning, transparency, and accountability. This study distinguishes these roles and introduces epistemic transparency as a measurable learning outcome in AI-mediated education.

The study's limitations include its cross-sectional design and its reliance on student self-reports. Future research could examine longitudinal data, other disciplines, or factors such as institutional policies. The study provides guidance for educators and institutions integrating GenAI while maintaining learning integrity.

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Declaration on the Use of AI The authors confirm that all aspects of the study—including the development, conceptualization, research design, review of literature, data collection, data analysis, interpretation of findings, and final conclusions—were done exclusively by the authors. Large language model-based AI tools were used only to enhance language quality, readability, sentence structure, and assist with the grammatical and stylistic editing of selected sections of the manuscript. AI tools were also used for limited brainstorming for wording and organization during manuscript preparation.

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Data Availability Statements The authors confirm that all data generated or analyzed during this study are included in this published article. To ensure data authenticity, the authors will provide the de-identified raw data and associated analytical codes together with the manuscript upon submission.

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