

# Modeling Generative AI Adoption in Higher Education: The Role of Interface Quality, Algorithmic Transparency, and Trust in Human-AI Interaction

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**Abstract.** This study examines generative artificial intelligence (AI) adoption in higher education by integrating interface quality, algorithmic transparency, and trust within a Human-AI Interaction framework. The study addresses limitations of traditional technology acceptance models, which often overlook psychological and relational factors in AI-enabled environments. Data were collected through a cross-sectional survey of 195 respondents, including students, lecturers, and administrative staff from higher education institutions in West Nusa Tenggara, Indonesia, within a cross-sectional regional sample, and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that Trust in AI is the strongest predictor of Behavioral Intention ( $\beta = 0.623$ ,  $p < 0.001$ ), followed by Perceived Usefulness ( $\beta = 0.270$ ,  $p < 0.05$ ). Interface Quality significantly affects Perceived Ease of Use ( $\beta = 0.803$ ), while Algorithmic Transparency strongly influences Perceived Control ( $\beta = 0.824$ ) and Perceived Usefulness ( $\beta = 0.562$ ). AI Anxiety was not found to have a significant direct or moderating effect. The model demonstrates substantial explanatory power ( $R^2 = 0.710$ ) and strong predictive relevance. This study proposes an integrated dual-path model combining cognitive and affective mechanisms to explain generative AI adoption in higher education. The findings emphasize that AI systems should be designed not only for functionality, but also for trust, transparency, and user confidence.

**Keywords:** Generative Artificial Intelligence; Higher Education; Human-AI Interaction; Trust in AI; Higher-Order Constructs; Hierarchical Component Model.

## 1. INTRODUCTION

Generative artificial intelligence is rapidly reshaping teaching and learning practices in higher education. Large language models and related generative tools are increasingly used to support writing, feedback, brainstorming, information retrieval, and personalized learning tasks, thereby altering how students access knowledge and complete academic work [1], [2]. At the same time, the educational value of generative AI is not determined solely by technical capability. Users' willingness to rely on these systems depends on how they experience interaction with AI, how understandable and transparent the system appears, and whether the system can be trusted in academic settings [3], [4]. This issue has become more urgent because generative AI systems are simultaneously perceived as useful learning aids and as potentially risky, opaque, or anxiety-inducing technologies [5], [6], [7]. As a result, understanding generative AI adoption in higher education requires a concise but more integrative framework that goes beyond conventional utility-based acceptance explanations and accounts for the relational and experiential qualities of human-AI interaction.

Existing research on AI adoption in education has provided important foundations, particularly through the use of Technology Acceptance Model (TAM), UTAUT, and related behavioral frameworks. Studies have shown that perceived usefulness and perceived ease of use remain robust predictors of intention to adopt AI tools in academic contexts [8], [9], [10]. Meta-analytic and review-based evidence similarly confirms that classic acceptance factors still matter in AI-related settings, although their relative influence may vary across contexts, user groups, and technological configurations [11], [12], [13]. Research on ChatGPT and other generative AI systems in universities has also identified the importance of pedagogical usefulness, digital readiness, support conditions, and individual attitudes toward AI [14], [15], [16]. Collectively, these studies establish a strong baseline for explaining generative AI adoption, but they still leave room for models that more explicitly capture the interactional, transparent, and trust-based nature of human-AI engagement in learning environments.

However, the current literature reveals several important limitations. First, many adoption studies in education still rely on broad behavioral variables while giving limited attention to the actual interaction qualities of AI systems. Yet generative AI is not merely another

software tool; it is an interactive, conversational, and adaptive partner whose interface design, feedback quality, responsiveness, and clarity may shape user judgments before usefulness is fully formed [17], [18], [19]. In higher education, students often evaluate AI through lived interaction based on how clearly the system presents information, how coherent its responses are, how professionally the interface is designed, and whether the interaction feels smooth and controllable [20], [21], [22]. Nevertheless, most education-focused AI adoption models do not conceptualize interface quality as a multidimensional construct that systematically explains downstream perceptions and intentions.

Second, although explainability and transparency are widely discussed in the AI ethics and human-centered AI literature, they have not been adequately integrated into student adoption models in higher education. Algorithmic transparency has been shown to influence perceptions of trustworthiness, fairness, accountability, and acceptance across multiple domains [23], [24], [25]. In educational settings, explainable AI has been positioned as essential for responsible, trustworthy, and pedagogically meaningful AI use [26], [27]. Recent reviews further suggest that educational AI systems should not only produce outputs but also communicate reasoning, limitations, and uncertainty in ways that support human understanding and responsible use [28], [29]. Even so, empirical studies in higher education have more often examined transparency conceptually than modeled it as a central determinant of student adoption behavior. Moreover, prior work frequently treats transparency in a narrow sense, focusing only on explanation or disclosure, rather than representing it as a richer construct encompassing explanation quality, process visibility, traceability, and uncertainty communication.

Third, trust has emerged as a central mechanism in AI acceptance, yet its role in educational adoption remains theoretically underdeveloped. Trust in AI is particularly important when users cannot fully verify outputs, when systems operate probabilistically, and when decisions involve intellectual or academic risk [30], [31], [32], [33]. In higher education, trust shapes whether students regard AI as a reliable aid, whether they are willing to incorporate AI outputs into assignments, and whether they critically engage with or passively accept machine-generated responses [34], [35]. Several studies have found that explainability, transparency, and social cues can influence trust, but the pathways remain mixed and context-dependent [36], [37]). Educational research has also noted that some students may trust AI too easily, whereas others remain skeptical or

anxious, suggesting that trust should be modeled as a dynamic psychological mechanism rather than a simple attitude [4], [38]. Yet many student-focused adoption studies still position trust as a secondary variable or omit it entirely.

Fourth, the broader human–AI interaction literature indicates that perceived control is essential for sustained and responsible collaboration with intelligent systems. When users feel able to direct, question, refine, or override AI outputs, they are more likely to experience autonomy, confidence, and appropriate reliance [39]. Perceived control has also been linked to trust formation, reduced uncertainty, and stronger behavioral intention in technology-enabled environments [40]. In explainable AI contexts, user control and transparency are often intertwined, because better explanations can help users feel more capable of understanding and managing system outputs [41]. Despite this, perceived control remains underexamined in generative AI adoption research in education, where the ability to steer prompts, revise outputs, and interpret responses is fundamental to meaningful learning use.

Fifth, recent scholarship has documented the growing relevance of AI anxiety as a psychological barrier to adoption. AI anxiety refers to discomfort, apprehension, or fear associated with using AI systems and has been linked to lower intention, greater technostress, and more negative attitudes toward AI [42], [43]. In educational settings, AI anxiety may be associated with concerns about dependency, loss of competence, replacement of human capabilities, or uncertainty about ethical and academic consequences [44]. Although some studies have examined direct effects of AI anxiety on intention or attitudes, fewer studies have investigated whether anxiety functions as a boundary condition that weakens otherwise positive relationships, such as the effect of trust on intention to use. This is an important omission because students may trust an AI system’s capability while still feeling sufficiently uneasy to limit their willingness to adopt it in ongoing learning activities.

Methodologically, prior research also shows a need for more sophisticated construct modeling. Both interface quality and algorithmic transparency are conceptually multidimensional phenomena that may be poorly represented when reduced to single first-order variables. The partial least squares structural equation modeling literature has increasingly recommended hierarchical component models for complex constructs

because they allow researchers to capture higher-level conceptual domains while preserving the specificity of their dimensions [45], [46]. Higher-order modeling has been successfully applied in several fields to represent multifaceted constructs with greater theoretical fidelity and measurement precision [47]. Yet educational AI adoption studies rarely operationalize interface quality or algorithmic transparency using hierarchical component models, even though such an approach is well suited to capturing the complexity of human-AI interaction. Overall, although prior studies have advanced the understanding of AI adoption in education, the literature remains fragmented in three key areas: cognitive acceptance variables are often emphasized more than interactional and experiential qualities; transparency, trust, and control are frequently examined separately rather than as an integrated human-AI interaction mechanism; and multidimensional constructs such as interface quality and algorithmic transparency are rarely modeled hierarchically while the moderating role of AI anxiety remains insufficiently examined. A few researchers have focused on generative AI acceptance among students and teachers using TAM - or UTAUT-based approaches [48].

Accordingly, the present study addresses these gaps by proposing an integrated model that combines interface quality, algorithmic transparency, trust, and perceived control within a Human-AI Interaction perspective. Specifically, this study aims to develop and test a generative AI adoption model in higher education that links interface quality and algorithmic transparency to behavioral intention through perceived ease of use, perceived usefulness, perceived control, and trust, while also examining AI anxiety as a moderating factor. The main contribution of this study lies in integrating cognitive, affective, and moderating mechanisms into a single TAM-Human-AI Interaction framework and in modeling interface quality and algorithmic transparency as higher-order constructs. By doing so, this study provides both theoretical insight into the mechanisms of generative AI adoption and practical guidance for designing AI systems that are functional, transparent, trustworthy, and user-centered in higher education.

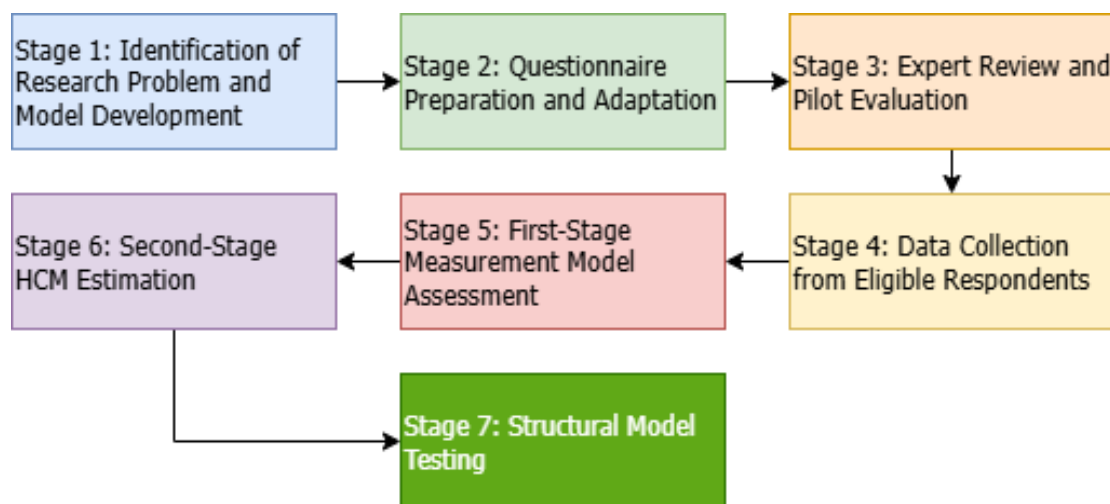
## **2. METHODS**

### **2.1. Research Design**

This study employed a quantitative approach using a cross-sectional survey design to investigate the determinants of generative AI adoption in higher education from a

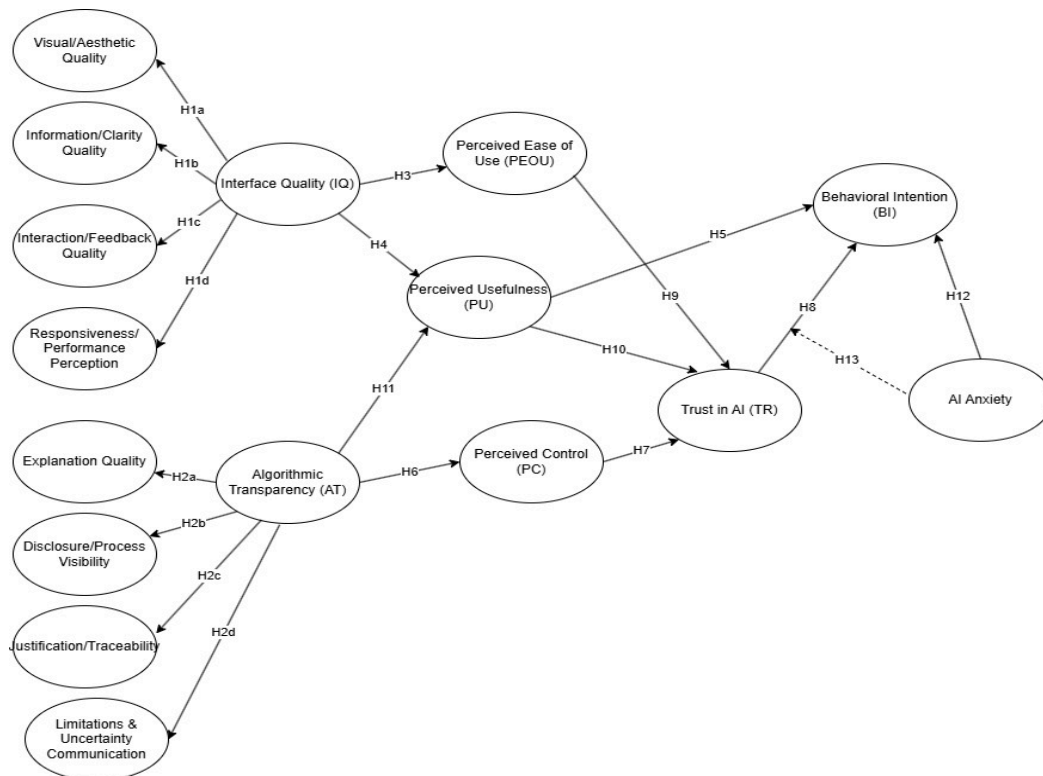
Human–AI Interaction perspective. This approach was appropriate because the study aimed to test a theoretically grounded structural model involving latent constructs, causal relationships, as well as mediating and moderating effects. Given the complexity of the proposed model and the inclusion of multidimensional constructs, Partial Least Squares Structural Equation Modeling (PLS-SEM) was utilized as the primary analytical technique. PLS-SEM is particularly suitable for predictive research, theory development, and models incorporating higher-order constructs [45], [46], [49]. The analysis was conducted using SmartPLS 4 software with a bootstrapping procedure of 10,000 subsamples to assess path significance, confidence intervals, and model robustness.

To improve methodological transparency, the research workflow consisted of several sequential stages: (1) identification of the research problem and model development, (2) questionnaire preparation and adaptation from prior literature, (3) expert review and pilot evaluation, (4) data collection from eligible respondents, (5) first-stage measurement model assessment, (6) second-stage hierarchical component model (HCM) estimation, and (7) structural model testing, including mediation and moderation analysis.



**Figure 1.** Research Workflow

Figure 1 summarizes the overall research procedure, beginning with model development and instrument preparation, followed by expert review, pilot testing, data collection, measurement-model assessment, HCM estimation, and structural model evaluation.



**Figure 1.** Conceptual Framework

The conceptual framework of this study, as illustrated in Figure 2, proposes an integrative TAM–HAI model of generative AI adoption in higher education. The framework combines perspectives from the Technology Acceptance Model (TAM) and Human–AI Interaction (HAI) and is structured around two complementary pathways, namely a cognitive route and an affective route, which jointly explain users' behavioral intention to use generative AI in academic contexts.

The cognitive route reflects a rational evaluation process derived from TAM. In this pathway, Interface Quality is positioned as an antecedent of Perceived Ease of Use and Perceived Usefulness. A well-designed interface enhances usability by reducing cognitive load and improving interaction efficiency, which in turn strengthens users' perception of usefulness. Subsequently, Perceived Usefulness is modeled as a direct predictor of Behavioral Intention. This pathway explains how users evaluate the functional benefits and ease of use of generative AI systems in supporting academic activities.

In contrast, the affective route emphasizes the psychological and relational aspects of human–AI interaction. Algorithmic Transparency is proposed to influence Perceived

Control, as transparent systems enable users to better understand, evaluate, and manage AI outputs. Increased perceived control fosters Trust in AI, which serves as a central mechanism driving Behavioral Intention. This pathway indicates that generative AI adoption is influenced not only by rational evaluation, but also by users' trust and perceived control over the system.

Beyond these primary pathways, the model incorporates cross-path relationships that reflect the integration of cognitive and affective mechanisms. Specifically, Perceived Ease of Use and Perceived Usefulness are hypothesized to influence Trust in AI, indicating that cognitive evaluations can contribute to trust formation. In addition, Algorithmic Transparency is proposed to have a direct effect on Perceived Usefulness, suggesting that transparent AI systems are perceived as more valuable and informative in learning contexts. Furthermore, the model includes AI Anxiety as a moderating variable in the relationship between Trust in AI and Behavioral Intention. AI Anxiety is conceptualized as a psychological condition that may weaken the positive influence of trust on intention. Even when users trust generative AI systems, high levels of anxiety may reduce their willingness to use such systems consistently in academic activities.

In this study, two key constructs Interface Quality and Algorithmic Transparency are modeled as higher-order constructs using a hierarchical component model approach. Interface Quality is represented by four lower-order dimensions: Visual/ Aesthetic Quality, Information/ Clarity Quality, Interaction/ Feedback Quality, and Responsiveness/ Performance Perception. These dimensions collectively capture the overall quality of the AI interface as experienced by users. Similarly, Algorithmic Transparency is conceptualized as a higher-order construct composed of Explanation Quality, Disclosure/Process Visibility, Justification/ Traceability, and Limitations and Uncertainty Communication. This multidimensional specification reflects the complex nature of transparency in AI systems and aligns with recent developments in explainable AI research.

The study was conducted in higher education institutions located in West Nusa Tenggara, Indonesia. Data were collected over a three-month period, from January to March 2026. The target population consisted of members of higher education institutions who had experience using generative AI tools for academic purposes, including students, lecturers,

and administrative staff. These activities included completing assignments, searching for information, generating ideas, drafting content, administrative support, and other learning-related or academic tasks. The final sample comprised 195 respondents, consisting of students (80.0%), lecturers (14.4%), and administrative staff (5.6%).

Although the survey was mainly distributed in higher education institutions within West Nusa Tenggara, 5 respondents, representing 2.56% of the total sample, were obtained from outside West Nusa Tenggara. These external responses were retained because they shared the same essential characteristics as the main sample, namely active engagement with generative AI in academic contexts, and represented only a minor proportion of the total dataset. To address possible concerns regarding regional heterogeneity, a sensitivity check was conducted by excluding these 5 outside-region respondents and re-estimating the structural model using the remaining 190 respondents from West Nusa Tenggara. The results remained substantively consistent with the full-sample analysis, with no meaningful changes in the direction, significance, or interpretation of the main path relationships. Accordingly, the empirical setting of the research remained higher education in West Nusa Tenggara.

A purposive sampling strategy was used to ensure that respondents met the substantive requirements of the study. Eligible participants were individuals within higher education institutions who had used generative AI applications in academic or work-related educational activities. This sampling approach is appropriate when the study requires respondents who possess specific experience relevant to the phenomenon under investigation. In this case, generative AI adoption could only be meaningfully assessed among respondents with actual exposure to AI-based tools. The survey was distributed through academic communication channels and institutional networks across participating institutions. Before completing the questionnaire, respondents were informed about the purpose of the study, the voluntary nature of participation, and the confidentiality of their responses. No personally identifying information was collected, and all responses were used only for academic research purposes.

All items were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The use of a five-point scale was considered appropriate because it provides sufficient discrimination while remaining simple and familiar for respondents

in survey-based educational research. Questionnaire items were adapted from validated measures reported in prior studies on TAM, trust in AI, interface quality, transparency, perceived control, and AI anxiety, then contextualized to the generative AI setting in higher education. Prior to full-scale distribution, the questionnaire was reviewed to ensure content clarity, contextual appropriateness, and wording consistency. The instrument was evaluated through expert review involving two academics in information systems and one methodological reviewer, followed by a pilot test with a small group of respondents to assess readability and item clarity. Minor wording refinements were then made before full deployment.

**Table 1.** Summary of Instrument Sources, Construct Dimensions, and Item Counts

Construct	Construct Type	Dimensions / Indicators	Item Count	Instrument Source
Interface Quality	Higher-order construct	Visual/ Aesthetic Quality; Information/ Clarity Quality; Interaction/ Feedback Quality; Responsiveness/ Performance Perception	12	Adapted from prior studies on interface quality, usability, and Human–AI Interaction [1], [17], [18], [21].
Algorithmic Transparency	Higher-order construct	Explanation Quality; Disclosure/ Process Visibility; Justification/ Traceability; Limitations and Uncertainty Communication	12	Adapted from prior studies on explainable AI, transparency, and responsible AI [23], [24], [27], [28], [53].
Perceived Ease of Use	First-order construct	Ease of interaction and perceived effort in using generative AI	4	Adapted from TAM-based studies [8], [9], [54].
Perceived Usefulness	First-order construct	Perceived academic utility and performance enhancement	4	Adapted from TAM-based studies [8], [9], [54].
Perceived Control	First-order construct	User agency, control, and ability to manage AI outputs	3	Adapted from Human–AI Interaction and perceived control studies [39], [40], [41], [55]

Construct	Construct Type	Dimensions / Indicators	Item Count	Instrument Source
Trust in AI	First-order construct	Reliability, confidence, and willingness to rely on AI outputs	4	Adapted from trust in AI and AI adoption studies [30], [31], [32].
Behavioral Intention	First-order construct	Intention to use generative AI in academic activities	4	Adapted from TAM and AI adoption studies [4], [8], [9], [54]
AI Anxiety	First-order construct	Discomfort, apprehension, and concern when using AI systems	3	Adapted from AI anxiety and technostress-related studies [5], [7], [42].

Table 1. summarizes the measurement instrument used in this study, including construct types, dimensions or conceptual indicators, item counts, and the main literature sources used for item adaptation. The two multidimensional constructs, namely Interface Quality and Algorithmic Transparency, were operationalized as higher-order constructs, while the remaining constructs were modeled as first-order reflective constructs.

The data analysis was conducted in two major stages using PLS-SEM. The first stage involved assessment of the measurement model. For the reflective lower-order and first-order constructs, the evaluation included indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Indicator reliability was assessed through outer loadings, with values above commonly accepted thresholds indicating that the indicators adequately represented their constructs. Internal consistency reliability was examined using Cronbach's alpha, composite reliability, and rho\_A. Convergent validity was evaluated using average variance extracted (AVE), while discriminant validity was assessed using the heterotrait-monotrait ratio (HTMT) and the Fornell–Larcker criterion. These procedures are consistent with current methodological guidance for PLS-SEM and are especially important in studies involving conceptually adjacent constructs such as trust, perceived control, transparency, and usefulness [45].

Because the model included two higher-order constructs, the hierarchical component model was estimated using a two-stage approach. This method is particularly appropriate when higher-order constructs are modeled from several reflective lower-order

components and when the research aims to retain both conceptual parsimony and dimensional precision [46], [49]. In the first stage, the lower-order constructs were estimated and validated. In the second stage, latent variable scores of the lower-order components were used to estimate the higher-order constructs of Interface Quality and Algorithmic Transparency. This procedure reduces model complexity while preserving the explanatory power of the multidimensional conceptualization.

The second stage involved assessment of the structural model. This included evaluating collinearity among predictor constructs through variance inflation factor (VIF), estimating path coefficients, and testing their significance using bootstrapping procedures. The explanatory power of the model was examined through the coefficient of determination ( $R^2$ ), while effect sizes ( $f^2$ ) were used to assess the substantive contribution of each exogenous construct to endogenous constructs. Predictive relevance was evaluated using  $Q^2$  values. In addition to the direct effects, the study also tested a moderation effect involving AI Anxiety and the relationship between Trust in AI and Behavioral Intention. The inclusion of moderation analysis was theoretically justified because anxiety may function as a boundary condition that alters the strength of intention formation in AI-related settings [50], [51], [52]. The interaction term was generated using the product-indicator approach within SmartPLS 4 and evaluated through bootstrapping to determine whether AI Anxiety weakened or altered the influence of trust on users' intention to adopt generative AI.

## 2.2. Hypothesis Development

Generative AI systems are characterized by complex, multi-dimensional interaction features that cannot be adequately captured using single-dimensional constructs. In line with the hierarchical component model (HCM) approach in PLS-SEM, higher-order constructs are commonly operationalized through multiple lower-order dimensions to better reflect conceptual richness and measurement validity [45], [46]. In the context of human-AI interaction, interface quality is not limited to usability but encompasses aesthetic appeal, clarity of information, feedback quality, and system responsiveness, all of which shape user experience and perception [1], [21]. Prior studies emphasize that well-designed interfaces enhance cognitive fluency and interaction satisfaction, which are critical in AI-assisted learning environments [17], [18]. Therefore, interface quality is conceptualized as a higher-order construct reflected by multiple dimensions:

- 1) H1a: Interface Quality positively influences Visual/Aesthetic Quality.
- 2) H1b: Interface Quality positively influences Information/Clarity Quality.
- 3) H1c: Interface Quality positively influences Interaction/Feedback Quality.
- 4) H1d: Interface Quality positively influences Responsiveness/Performance Perception.

Similarly, algorithmic transparency has been recognized as a multi-dimensional construct in explainable AI research. Transparency extends beyond simple disclosure and includes explanation quality, process visibility, justification, and communication of limitations and uncertainty [23], [27]. Studies show that users are more likely to accept AI systems when they understand how outputs are generated and when systems communicate reasoning and uncertainty clearly [24], [53]. In educational contexts, explainable AI is essential for fostering responsible and critical use of AI-generated content [28]. Thus, algorithmic transparency is modeled as a higher-order construct composed of several dimensions:

- 1) H2a: Algorithmic Transparency positively influences Explanation Quality.
- 2) H2b: Algorithmic Transparency positively influences Disclosure/Process Visibility.
- 3) H2c: Algorithmic Transparency positively influences Justification/Traceability.
- 4) H2d: Algorithmic Transparency positively influences Limitations & Uncertainty Communication.

From the perspective of the Technology Acceptance Model (TAM), perceived ease of use and perceived usefulness remain central determinants of technology adoption [54]. In AI-based systems, interface quality plays a critical role in shaping ease of use, as intuitive, responsive, and well-structured interfaces reduce cognitive load and enhance usability [21]. Moreover, interface quality can also influence perceived usefulness, although this relationship is often weaker because usefulness depends on both system capability and user goals [8]. Therefore:

- 1) H3: Interface Quality positively influences Perceived Ease of Use.
- 2) H4: Interface Quality positively influences Perceived Usefulness.

Perceived usefulness is widely recognized as a key predictor of behavioral intention to use technology, including AI systems in education [9]. When students perceive generative

AI as beneficial for improving learning efficiency, performance, and outcomes, they are more likely to adopt it [4]. Thus:

H5: Perceived Usefulness positively influences Behavioral Intention.

In human–AI interaction, algorithmic transparency is closely associated with perceived control. When users understand how AI systems operate, they feel more capable of managing, evaluating, and directing system outputs [55]. Prior research indicates that transparency enhances user agency and reduces uncertainty, thereby strengthening perceived control in AI interactions [41]. Therefore:

H6: Algorithmic Transparency positively influences Perceived Control.

Perceived control has been identified as a key determinant of trust in AI systems. Users who feel in control of interactions are more likely to develop confidence in the system and rely on its outputs [40]. In AI-assisted environments, control mitigates uncertainty and enhances psychological comfort, which are essential for trust formation. Thus:

H7: Perceived Control positively influences Trust in AI.

Trust is a central mechanism in AI adoption, particularly in contexts characterized by uncertainty and limited transparency. Numerous studies have shown that trust significantly influences users' willingness to rely on AI systems and integrate them into decision-making processes [30], [31]. In educational settings, trust determines whether students accept AI-generated outputs and incorporate them into learning activities [4]. Therefore:

H8: Trust in AI positively influences Behavioral Intention.

In addition to perceived control, trust can also be shaped by cognitive evaluations such as perceived ease of use and perceived usefulness. Systems that are easy to use are perceived as more predictable and reliable, thereby fostering trust [21]. Similarly, when users perceive AI systems as useful and effective, they are more likely to trust their outputs [56]. Therefore:

- 1) H9: Perceived Ease of Use positively influences Trust in AI.
- 2) H10: Perceived Usefulness positively influences Trust in AI.

Furthermore, algorithmic transparency may also influence perceived usefulness. Transparent systems provide meaningful explanations and insights, which can enhance users' perception of value and utility [53]. In educational contexts, explainability enables students to better understand AI outputs and apply them effectively, thereby increasing perceived usefulness [29]. Thus:

H11: Algorithmic Transparency positively influences Perceived Usefulness.

Finally, psychological factors such as AI anxiety may influence adoption behavior. AI anxiety has been shown to negatively affect users' attitudes and intention to use AI technologies [5], [7]. Individuals who experience higher levels of anxiety may avoid using AI systems or limit their engagement. Moreover, anxiety may weaken the positive effect of trust on behavioral intention, as users may hesitate to act on their trust due to underlying concerns. Therefore:

- 1) H12: AI Anxiety negatively influences Behavioral Intention.
- 2) H13: AI Anxiety moderates the relationship between Trust in AI and Behavioral Intention, such that the relationship is weaker when AI Anxiety is higher.

### 3. RESULTS AND DISCUSSION

#### 3.1. Respondent Characteristics

The demographic profile of the respondents is presented in Table 2. The sample consisted of 195 participants, with a relatively balanced gender distribution, comprising 99 males (50.8%) and 96 females (49.2%). This balance indicates that the findings are not biased toward a particular gender group and may reasonably reflect diverse user perspectives in generative AI adoption. In terms of age, the majority of respondents were relatively young, with 39.0% aged below 20 years and 34.4% between 20 and 25 years. A smaller proportion of respondents were aged 26–30 years (4.6%), while 22.1% were above 30 years. This distribution suggests that the sample is dominated by younger individuals, which is consistent with the typical demographic profile of active users of digital technologies and generative AI in educational contexts.

**Table 2.** Respondent Characteristics (N = 195)

Characteristics	Category	Frequency (n)	Percentage (%)
Gender	Male	99	50.8
	Female	96	49.2
Age	< 20 years	76	39.0
	20–25 years	67	34.4
	26–30 years	9	4.6
	> 30 years	43	22.1
Respondent Status	Students	156	80.0
	Lecturers	28	14.4
	Administrative Staff	11	5.6
AI Usage Experience	< 6 months	38	19.5
	6–12 months	55	28.2
	> 1 year	102	52.3
Frequency of AI Usage	Rarely	17	8.7
	Occasionally	81	41.5
	Frequently	84	43.1
	Very frequently	13	6.7
Type of AI Used	ChatGPT	145	74.4
	Google Gemini	29	14.9
	Microsoft Copilot	3	1.5
	Others	18	9.2
Total		<b>195</b>	<b>100</b>

Regarding respondent status, most participants were students (80.0%), followed by lecturers (14.4%) and administrative staff (5.6%). This composition is consistent with the revised scope of the study, which examines generative AI adoption in higher education rather than student learning alone. The inclusion of lecturers and administrative staff, although limited, provides additional contextual variation and reflects a broader academic environment. With respect to AI usage experience, more than half of the respondents (52.3%) reported having used generative AI for more than one year, indicating a relatively high level of familiarity with AI tools. Meanwhile, 28.2% had used AI for 6–12 months, and 19.5% had less than six months of experience. This distribution

suggests that the majority of respondents have sufficient experience to provide informed evaluations of generative AI systems.

In terms of usage frequency, most respondents reported frequent interaction with AI tools. Specifically, 43.1% indicated that they used AI frequently, and 41.5% reported occasional use. Only a small proportion of respondents used AI rarely (8.7%) or very frequently (6.7%). This pattern reflects regular engagement with AI systems in academic activities, supporting the relevance of the sample for examining behavioral intention and usage patterns. Finally, regarding the type of AI tools used, ChatGPT was the most dominant platform, reported by 74.4% of respondents. This was followed by Google Gemini (14.9%), while a very small proportion used Microsoft Copilot (1.5%) or other AI tools (9.2%). The dominance of ChatGPT indicates that it is the primary generative AI tool used in the academic context of this study, which is consistent with global trends in AI adoption in education.

### 3.2. Measurement Model Assessment

The measurement model was evaluated to ensure the reliability and validity of the constructs prior to testing the structural relationships. This evaluation includes indicator reliability, internal consistency reliability, convergent validity, and discriminant validity, following the guidelines of PLS-SEM literature.

#### 3.2.1. Indicator Reliability

As presented in Table 3, all indicator loadings exceed the recommended threshold of 0.70, indicating satisfactory indicator reliability. The outer loadings range from 0.780 to 0.924. The lowest loading is observed in AA1 (0.780), which remains acceptable as it exceeds the minimum threshold of 0.70, while the highest loading is found in PU4 (0.924), demonstrating strong representation of the construct. These results confirm that all measurement items adequately reflect their respective latent constructs and no indicator removal was necessary.

**Table 3.** Measurement Model Assessment (Outer Loadings)

Construct	Indicator	Code	Outer Loading
Visual/ Aesthetic Quality	AI interface is visually appealing	VAQ1	0.863
	Consistent colors and typography	VAQ2	0.874

Construct	Indicator	Code	Outer Loading
	Professional interface design	VAQ3	0.889
Information/ Clarity Quality	Information is easy to understand	ICQ1	0.877
	Information structure is clear	ICQ2	0.895
	Instructions are clearly presented	ICQ3	0.885
Interaction/ Feedback Quality	Responses match user input	IFQ1	0.868
	Feedback is helpful and relevant	IFQ2	0.881
	Interaction feels responsive	IFQ3	0.869
Responsiveness/ Performance Perception	AI responds quickly	RPP1	0.872
	System rarely experiences errors	RPP2	0.901
	Performance is stable	RPP3	0.874
Explanation Quality	Explains reasoning behind responses	EQ1	0.872
	Explanations are easy to understand	EQ2	0.827
	Provides contextual explanations	EQ3	0.891
Disclosure/ Process Visibility	Processing mechanism is understandable	DPV1	0.888
	System operates transparently	DPV2	0.882
	Shows how outputs are generated	DPV3	0.845
Justification/ Traceability	Provides justification for responses	JT1	0.835
	Reasoning is traceable	JT2	0.875
	Sources or logic are shown	JT3	0.841
Limitations & Uncertainty Communication	Communicates response limitations	LUC1	0.860
	Acknowledges uncertainty	LUC2	0.816
	Indicates possible errors	LUC3	0.897
Perceived Ease of Use	Easy to learn	PEOU1	0.851
	Requires minimal effort	PEOU2	0.866
	Easy for academic tasks	PEOU3	0.801
	Easy to operate AI system	PEOU4	0.870
Perceived Usefulness	Improves learning efficiency	PU1	0.891
	Helps complete tasks faster	PU2	0.907
	Enhances work quality	PU3	0.904
	Useful for academic activities	PU4	0.924
Perceived Control	I feel in control	PC1	0.858
	I can direct the AI	PC2	0.854
	I can refine outputs	PC3	0.863
	I can control AI interaction	PC4	0.847
Trust in AI	Provides accurate information	TR1	0.851

Construct	Indicator	Code	Outer Loading
	AI is reliable	TR2	0.861
	Feels safe to use	TR3	0.847
	Confident using AI for tasks	TR4	0.908
Behavioral Intention	Intend to continue using	BI1	0.904
	Will recommend to others	BI2	0.898
	Plan to use regularly	BI3	0.908
	Intend to increase AI usage	BI4	0.887
AI Anxiety	Feel anxious using AI	AA1	0.780
	Concerned about replacement	AA2	0.817
	Uncomfortable relying on AI	AA3	0.842
	Concerned AI affects thinking ability	AA4	0.848

### 3.2.2. Internal Consistency Reliability and Convergent Validity

The results of internal consistency reliability and convergent validity are presented in Table 4. All constructs demonstrate Cronbach's alpha (CA) and Composite Reliability (CR) values above the recommended threshold of 0.70, indicating high internal consistency. Specifically, CA values range from 0.840 (AI Anxiety) to 0.946 (Algorithmic Transparency), while CR values range from 0.893 to 0.953.

**Table 4.** Construct Reliability and Convergent Validity

Construct	CA	rho_A	CR	AVE
Visual/Aesthetic Quality (VAQ)	0.847	0.849	0.908	0.766
Information/Clarity Quality (ICQ)	0.863	0.864	0.916	0.785
Interaction/Feedback Quality (IFQ)	0.843	0.843	0.905	0.761
Responsiveness/Performance Perception (RPP)	0.858	0.859	0.914	0.779
Explanation Quality (EQ)	0.877	0.881	0.924	0.802
Disclosure/Process Visibility (DPV)	0.876	0.878	0.924	0.801
Justification/Traceability (JT)	0.849	0.852	0.909	0.769
Limitations & Uncertainty Communication (LUC)	0.872	0.875	0.921	0.796
Interface Quality (IQ) (HOC)	0.945	0.945	0.952	0.622
Algorithmic Transparency (AT) (HOC)	0.946	0.947	0.953	0.630
Perceived Ease of Use (PEOU)	0.869	0.877	0.911	0.718
Perceived Usefulness (PU)	0.928	0.929	0.949	0.822

Construct	CA	rho_A	CR	AVE
Perceived Control (PC)	0.878	0.878	0.916	0.732
Trust in AI (TR)	0.890	0.893	0.924	0.752
Behavioral Intention (BI)	0.921	0.922	0.944	0.808
AI Anxiety (AA)	0.840	0.845	0.893	0.676

**Note(s):** CA = Cronbach's Alpha; rho\_A = Dijkstra–Henseler's rho; CR = Composite Reliability; AVE = Average Variance Extracted; HOC = Higher-Order Construct.

Additionally, rho\_A values for all constructs exceed 0.70, further confirming reliability. Convergent validity is supported as all Average Variance Extracted (AVE) values exceed the threshold of 0.50. The AVE values range from 0.622 (Interface Quality) to 0.822 (Perceived Usefulness), indicating that each construct explains more than 50% of the variance in its indicators. Notably, the higher-order constructs (HOC), namely Interface Quality (IQ) and Algorithmic Transparency (AT), exhibit slightly lower AVE values (0.622 and 0.630, respectively) compared to first-order constructs. However, these values remain above the acceptable threshold and are theoretically justified, as HOCs aggregate multiple dimensions, which naturally increases variance heterogeneity. Therefore, the convergent validity of both 2778OC sis considered satisfactory.

### 3.2.3. Discriminant Validity: HTMT Criterion

Discriminant validity was first assessed using the Heterotrait–Monotrait Ratio (HTMT), as shown in Table 5. Most HTMT values among the lower-order and conceptually distinct first-order constructs are below the conservative threshold of 0.90, indicating acceptable discriminant validity at the substantive construct level. However, several HTMT values exceed 0.90 and even 1.00, particularly in comparisons involving the higher-order constructs and their own dimensions, such as Interface Quality with ICQ (1.005) and IFQ (1.019), as well as Algorithmic Transparency with JT (1.013).

These values should be interpreted carefully. In a hierarchical component model, very high HTMT values between a higher-order construct and its constituent lower-order dimensions are structurally expected because they share substantial variance by design. Therefore, these comparisons are not conceptually equivalent to comparisons between independent constructs such as Perceived Usefulness, Trust in AI, and Behavioral Intention. For this reason, the more meaningful interpretation of Table 5 lies in the

discriminant validity among distinct first-order constructs, whereas the overlap between HOCs and their dimensions is treated as an inherent feature of the higher-order specification rather than as evidence of construct redundancy.

**Table 5.** Discriminant Validity (HTMT Criterion)

Construct	VAQ	ICQ	IFQ	RPP	EQ	DPV	JT	LUC	IQ	AT	PEOU	PU	PC	TR	BI	AA	AAxTR
VAQ	-																
ICQ	0.892	-															
IFQ	0.866	0.928	-														
RPP	0.830	0.813	0.871	-													
EQ	0.802	0.841	0.914	0.870	-												
DPV	0.810	0.782	0.763	0.863	0.814	-											
JT	0.787	0.763	0.772	0.807	0.835	0.913	-										
LUC	0.804	0.782	0.763	0.750	0.781	0.823	0.851	-									
IQ	0.998	1.005	1.019	0.975	0.907	0.852	0.829	0.821	-								
AT	0.861	0.852	0.864	0.885	0.960	0.992	1.013	0.968	0.917	-							
PEOU	0.806	0.812	0.864	0.832	0.880	0.765	0.836	0.799	0.878	0.881	-						
PU	0.734	0.794	0.838	0.790	0.906	0.762	0.830	0.748	0.836	0.872	0.884	-					
PC	0.764	0.740	0.848	0.787	0.874	0.844	0.831	0.808	0.831	0.902	0.884	0.904	-				
TR	0.828	0.803	0.868	0.837	0.934	0.829	0.875	0.830	0.884	0.932	0.941	0.963	0.938	-			
BI	0.710	0.715	0.778	0.650	0.825	0.705	0.693	0.664	0.755	0.776	0.810	0.852	0.849	0.917	-		
AA	0.434	0.353	0.443	0.485	0.560	0.523	0.566	0.466	0.454	0.568	0.570	0.545	0.620	0.570	0.433	-	
AA × TR	0.328	0.367	0.390	0.415	0.469	0.427	0.414	0.382	0.397	0.455	0.459	0.423	0.405	0.417	0.359	0.197	-

**Note(s):** VAQ = Visual/Aesthetic Quality; ICQ = Information/Clarity Quality; IFQ = Interaction/Feedback Quality; RPP = Responsiveness/Performance Perception; EQ = Explanation Quality; DPV = Disclosure/Process Visibility; JT = Justification/Traceability; LUC = Limitations & Uncertainty Communication; IQ = Interface Quality; AT = Algorithmic Transparency; PEOU = Perceived Ease of Use; PU = Perceived Usefulness; PC = Perceived Control; TR = Trust in AI; BI = Behavioral Intention; AA = AI Anxiety.

At the same time, Table 5 also indicates that some conceptually adjacent first-order constructs, such as Perceived Usefulness, Perceived Control, and Trust in AI, are strongly correlated. This pattern suggests that users evaluate generative AI not only through isolated dimensions, but through interconnected cognitive and affective judgments. Nevertheless, these constructs remain theoretically distinguishable in the model because they play different explanatory roles: usefulness reflects instrumental value, control reflects user agency, and trust reflects confidence in the system.

### 3.2.4. Discriminant Validity: Fornell–Larcker Criterion

Further assessment of discriminant validity was conducted using the Fornell–Larcker criterion, as presented in Table 6. The square root of AVE for each construct (diagonal values) is generally higher than its correlations with other constructs, supporting discriminant validity.

**Table 6.** Discriminant Validity (Fornell–Larcker Criterion)

Construct	VAQ	ICQ	IFQ	RPP	EQ	DPV	JT	LUC	IQ	AT	PEOUPU	PC	TR	BI	AA
VAQ	0.875														
ICQ	0.765	0.886													
IFQ	0.733	0.792	0.873												
RPP	0.708	0.701	0.743	0.883											
EQ	0.692	0.731	0.786	0.753	0.896										
DPV	0.697	0.680	0.656	0.748	0.715	0.895									
JT	0.666	0.654	0.652	0.689	0.723	0.789	0.877								
LUC	0.691	0.678	0.652	0.649	0.685	0.719	0.733	0.892							
IQ	0.891	0.909	0.911	0.877	0.825	0.774	0.741	0.744	0.789						
AT	0.770	0.769	0.771	0.797	0.878	0.904	0.908	0.877	0.865	0.794					
PEOU	0.698	0.711	0.747	0.727	0.772	0.674	0.723	0.699	0.803	0.805	0.848				
PU	0.650	0.710	0.743	0.704	0.817	0.688	0.737	0.674	0.783	0.819	0.801	0.907			
PC	0.658	0.645	0.730	0.685	0.770	0.741	0.718	0.707	0.757	0.824	0.778	0.818	0.855		
TR	0.719	0.704	0.752	0.730	0.825	0.732	0.759	0.732	0.809	0.855	0.833	0.877	0.830	0.867	
BI	0.628	0.638	0.686	0.579	0.744	0.634	0.613	0.596	0.706	0.726	0.731	0.789	0.764	0.832	0.899
AA	0.366	0.301	0.374	0.413	0.483	0.450	0.480	0.403	0.405	0.510	0.485	0.483	0.538	0.496	0.384

**Note(s):** VAQ = Visual/Aesthetic Quality; ICQ = Information/Clarity Quality; IFQ = Interaction/Feedback Quality; RPP = Responsiveness/Performance Perception; EQ = Explanation Quality; DPV = Disclosure/Process Visibility; JT = Justification/Traceability; LUC = Limitations & Uncertainty Communication; IQ = Interface Quality; AT = Algorithmic Transparency; PEOU = Perceived Ease of Use; PU = Perceived Usefulness; PC = Perceived Control; TR = Trust in AI; BI = Behavioral Intention; AA = AI Anxiety.

However, similar to the HTMT results, some overlaps are observed in constructs related to higher-order dimensions. For instance, Interface Quality shows higher correlations with certain lower-order constructs (e.g., ICQ = 0.909 and IFQ = 0.911) compared to its square root of AVE (0.789). A similar pattern is observed for Algorithmic Transparency with DPV (0.904) and JT (0.908), exceeding its AVE square root (0.794). Rather than treating

these results as ordinary discriminant validity violations, they should be interpreted within the logic of the hierarchical component model, where the higher-order construct is estimated from its lower-order dimensions. Accordingly, the overlap is strongest exactly where conceptual and statistical nesting is expected.

More importantly, the Fornell–Larcker results among the conceptually distinct substantive constructs such as PEOU, PU, PC, TR, BI, and AA remain broadly interpretable and support the structural analysis. Although some correlations are high, especially between PU and TR or PC and TR, they do not collapse into a single construct because each retains distinct theoretical meaning and empirical function within the proposed dual-path model. Thus, the discriminant validity evidence should be read at the appropriate construct level: lower-order and distinct substantive constructs are the primary basis for evaluation, whereas HOC–LOC overlap is interpreted as a consequence of hierarchical specification.

To further clarify the discriminant validity evidence, the high HTMT and Fornell–Larcker overlaps involving Interface Quality, Algorithmic Transparency, and their respective lower-order dimensions should be interpreted within the logic of the hierarchical component model rather than as ordinary discriminant validity violations. In this study, Interface Quality and Algorithmic Transparency were intentionally specified as higher-order constructs formed from conceptually related lower-order dimensions. Therefore, strong empirical overlap between the HOCs and their LOCs is theoretically expected because these dimensions are designed to represent the broader construct domain. However, the substantive first-order constructs, such as Perceived Ease of Use, Perceived Usefulness, Perceived Control, Trust in AI, Behavioral Intention, and AI Anxiety, remain theoretically separable because they capture different mechanisms in the proposed dual-path model. Perceived Usefulness reflects instrumental value, Perceived Control reflects user agency, Trust in AI reflects confidence and willingness to rely on the system, while Behavioral Intention represents users' future adoption tendency. Empirically, the constructs also remain distinguishable because the outer loadings, reliability values, AVE values, and structural paths support their distinct measurement and explanatory roles. As a robustness statement, the interpretation of the model is not based solely on HTMT values involving HOC–LOC relationships, but on the combined evidence from indicator reliability, convergent validity, Fornell–Larcker results, theoretical construct definitions,

and the differentiated structural effects observed in the model. Thus, although high associations appear among conceptually adjacent constructs, the overall evidence supports the theoretical and empirical separability of the main constructs used in this study.

Taken together, the measurement model demonstrates satisfactory reliability and convergent validity, while discriminant validity requires a nuanced interpretation due to the presence of two higher-order constructs. The high overlap between HOCs and their lower-order dimensions is consistent with the hierarchical specification of the model and does not necessarily indicate construct redundancy. Moreover, the main substantive constructs remain theoretically and empirically distinguishable based on their conceptual definitions, measurement properties, and differentiated structural roles. Accordingly, the results support continuation to structural model analysis, but the overlap between certain higher-order and lower-order components is acknowledged as a methodological characteristic of the model rather than ignored.

### 3.3. Structural Model Results and Discussion

The structural model was evaluated by examining the coefficient of determination ( $R^2$ ), predictive relevance ( $Q^2$ ), path coefficients ( $\beta$ ), effect sizes ( $F^2$ ), and collinearity diagnostics (VIF). The results of the structural model quality are presented in Table 7, while the hypothesis testing results are summarized in Table 8.

#### 3.3.1. Structural Model Quality and Predictive Power

As shown in Table 7, the model demonstrates strong explanatory power across most endogenous constructs. The  $R^2$  values for first-order constructs such as Visual/Aesthetic Quality (0.795), Information/Clarity Quality (0.827), Interaction/Feedback Quality (0.831), and Disclosure/Process Visibility (0.818) fall within the substantial range, indicating that Interface Quality and Algorithmic Transparency strongly explain their respective dimensions.

**Table 7.** Structural Model Quality and Predictive Relevance

Endogenous Construct	$R^2$	Adj. $R^2$	Interpretation ( $R^2$ )	$Q^2$	Interpretation ( $Q^2$ )
Visual/Aesthetic Quality	0.795	0.794	Substantial	0.602	Large

Endogenous Construct	R <sup>2</sup>	Adj. R <sup>2</sup>	Interpretation (R <sup>2</sup> )	Q <sup>2</sup>	Interpretation (Q <sup>2</sup> )
Information/Clarity Quality	0.827	0.826	Substantial	0.641	Large
Interaction/Feedback Quality	0.831	0.830	Substantial	0.625	Large
Responsiveness/Performance Perception	0.770	0.769	Substantial	0.595	Large
Explanation Quality	0.770	0.769	Substantial	0.608	Large
Disclosure/Process Visibility	0.818	0.817	Substantial	0.649	Large
Justification/Traceability	0.825	0.824	Substantial	0.629	Large
Limitations & Uncertainty Communication	0.770	0.769	Substantial	0.608	Large
Perceived Ease of Use	0.645	0.643	Moderate	0.449	Large
Perceived Usefulness	0.692	0.689	Moderate	0.564	Large
Perceived Control	0.678	0.677	Moderate	0.491	Large
Trust in AI	0.832	0.830	Substantial	0.616	Large
Behavioral Intention	0.710	0.704	Moderate	0.560	Large

**Note(s):** R<sup>2</sup> = Variance explained; Adjusted R<sup>2</sup> = Adjusted coefficient of determination; Q<sup>2</sup> = Predictive relevance (Stone–Geisser criterion).

Similarly, Trust in AI exhibits a high R<sup>2</sup> value of 0.832, suggesting that it is well explained by Perceived Control, Perceived Ease of Use, and Perceived Usefulness. Behavioral Intention shows an R<sup>2</sup> value of 0.710, which is categorized as moderate to substantial, indicating that the model captures a significant proportion of variance in users' intention to use generative AI. In terms of predictive relevance, all Q<sup>2</sup> values exceed zero and are classified as large, ranging from 0.449 to 0.649. This confirms that the model has strong predictive capability and is not only explanatory but also robust in predicting endogenous constructs. Analytically, Table 7 shows that the model performs particularly well in explaining trust formation and the dimensions of the two higher-order constructs, while the explanatory power for usefulness, control, and intention remains moderate but still substantial for behavioral research in technology adoption. These results suggest that the proposed framework is especially strong in capturing upstream evaluative mechanisms that later translate into behavioral intention.

### 3.3.2. Effects of Interface Quality (IQ)

The results in Table 8 indicate that Interface Quality has a strong and significant effect on all its dimensions, including Visual/Aesthetic Quality ( $\beta = 0.891$ ), Information/ Clarity Quality ( $\beta = 0.909$ ), Interaction/ Feedback Quality ( $\beta = 0.911$ ), and Responsiveness/

Performance Perception ( $\beta = 0.877$ ), all with large effect sizes. These findings confirm that Interface Quality is a well-defined higher-order construct that strongly reflects its underlying dimensions. Furthermore, Interface Quality significantly influences Perceived Ease of Use ( $\beta = 0.803$ , large effect), suggesting that well-designed AI interfaces reduce user effort and cognitive load. However, its direct effect on Perceived Usefulness is relatively weaker ( $\beta = 0.297$ , small effect). This difference is theoretically meaningful. It indicates that interface quality primarily shapes usability judgments first, whereas usefulness judgments depend not only on interface design but also on whether the AI system produces relevant, accurate, and academically valuable outputs. In other words, a system may be easy and pleasant to use without necessarily being perceived as highly useful for substantive academic tasks.

**Table 8.** Structural Model Results and Hypothesis Testing

Hypothesis/ Relationship	$\beta$	t-value	p-value	F <sup>2</sup>	Effect Size	VIF	Result
H1a: IQ → VAQ	0.891	42,754	0.000	3,869	Large	1,000	Supported
H1b: IQ → ICQ	0.909	54,459	0.000	4,785	Large	1,000	Supported
H1c: IQ → IFQ	0.911	56,482	0.000	4,901	Large	1,000	Supported
H1d: IQ → RPP	0.877	37,759	0.000	3,347	Large	1,000	Supported
H2a: AT → EQ	0.878	29,830	0.000	3,349	Large	1,000	Supported
H2b: AT → DPV	0.904	43,241	0.000	4,485	Large	1,000	Supported
H2c: AT → JT	0.908	48,606	0.000	4,725	Large	1,000	Supported
H2d: AT → LUC	0.877	34,973	0.000	3,343	Large	1,000	Supported
H3: IQ → PEOU	0.803	23,491	0.000	1,819	Large	1,000	Supported
H4: IQ → PU	0.297	2,581	0.010	0.072	Small	3,980	Supported
H5: PU → BI	0.270	2,555	0.011	0.056	Small	4,481	Supported
H6: AT → PC	0.824	19,961	0.000	2,109	Large	1,000	Supported
H7: PC → TR	0.234	3,538	0.000	0.094	Small	3,472	Supported
H8:TR → BI	0.623	6,207	0.000	0.298	Medium	4,499	Supported
H9: PEOU → TR	0.283	4,551	0.000	0.150	Small	3,192	Supported
H10: PU → TR	0.459	7,464	0.000	0.329	Medium	3,814	Supported
H11: AT → PU	0.562	4,333	0.000	0.258	Medium	3,980	Supported
H12: AA → BI	-0.055	0.914	0.361	0.008	Negligible	1,346	Not Supported
H13: AA × TR → BI	0.000	0.012	0.990	0.000	Negligible	1,209	Not Supported

**Note(s):**  $\beta$  = Path coefficient;  $F^2$  = Effect size; VIF = Variance Inflation Factor. Significance level:  $p < 0.05$ .

### 3.3.3. Effects of Algorithmic Transparency (AT)

Algorithmic Transparency shows a strong and significant impact on all its dimensions, including Explanation Quality ( $\beta = 0.878$ ), Disclosure/Process Visibility ( $\beta = 0.904$ ), Justification/Traceability ( $\beta = 0.908$ ), and Limitations and Uncertainty Communication ( $\beta = 0.877$ ), all with large effect sizes. These results validate the multidimensional nature of transparency as a higher-order construct. Moreover, Algorithmic Transparency significantly influences Perceived Control ( $\beta = 0.824$ , large effect) and Perceived Usefulness ( $\beta = 0.562$ , medium effect). This suggests that transparent AI systems enhance users' sense of control and improve their perception of usefulness. The stronger effect of transparency on control than on usefulness is particularly important. It implies that transparency first works by making users feel more capable of understanding and managing AI outputs, and only then contributes to utility judgments. This supports the affective route of the model, where understanding and controllability serve as psychological foundations for subsequent trust formation.

### 3.3.4. Cognitive and Affective Drivers of Trust

Trust in AI is influenced by multiple factors, including Perceived Control ( $\beta = 0.234$ ), Perceived Ease of Use ( $\beta = 0.283$ ), and Perceived Usefulness ( $\beta = 0.459$ ). Among these, Perceived Usefulness has the strongest effect, indicating that users are more likely to trust AI systems when they perceive them as beneficial for academic tasks. These findings highlight that trust is not solely an affective construct but is also shaped by cognitive evaluations. The integration of usability, usefulness, and control into trust formation reflects the hybrid nature of Human–AI Interaction, where both rational and psychological factors jointly determine user trust. At the same time, the relatively high intercorrelations among usefulness, control, and trust suggest that these constructs are closely connected in generative AI use. Nevertheless, their effects are not identical. Usefulness contributes the strongest explanatory role in trust formation, indicating that users tend to trust AI when it demonstrably helps them perform academic work better. Perceived control contributes more modestly, suggesting that feeling able to direct or refine AI outputs enhances trust, but does not replace the importance of perceived value. This distinction supports the argument that trust in generative AI emerges from both

instrumental evaluation and relational assurance, rather than from a single psychological source.

### 3.3.5. Determinants of Behavioral Intention

Behavioral Intention is primarily driven by Trust in AI ( $\beta = 0.623$ , medium effect), which is the strongest predictor in the model. This finding underscores the central role of trust in the adoption of generative AI, particularly in educational settings where users rely on AI outputs for learning activities. Perceived Usefulness also has a significant but weaker effect on Behavioral Intention ( $\beta = 0.270$ ), suggesting that usefulness alone is not sufficient to drive continued use. Instead, trust emerges as a more critical determinant, reinforcing the importance of psychological assurance in AI adoption. This pattern also clarifies the distinctiveness of the proposed dual-path model. The cognitive route remains important because usefulness significantly predicts intention, but the affective route becomes more decisive once users must decide whether to continue relying on AI in academic settings. Thus, users may recognize a system as useful, yet still withhold full behavioral commitment unless they consider it trustworthy.

### 3.3.6. Role of AI Anxiety

Contrary to expectations, AI Anxiety does not have a significant direct effect on Behavioral Intention ( $\beta = -0.055$ ,  $p = 0.361$ ), nor does it moderate the relationship between Trust in AI and Behavioral Intention ( $\beta = 0.000$ ,  $p = 0.990$ ). These findings suggest that, within the context of this study, anxiety does not play a significant role in influencing AI adoption behavior. This non-significant result should not be interpreted merely as an absence of psychological barriers, but rather as a context-dependent finding that may reflect several conditions in the present sample. One possible explanation is that respondents, who are predominantly experienced users, have already developed familiarity with AI technologies, thereby reducing anxiety-related concerns. This interpretation is supported by the respondent profile, where more than half had used generative AI for over one year and most reported occasional to frequent use. Alternatively, the increasing normalization of AI tools in education may have diminished the psychological barriers associated with their use.

A second possible explanation is measurement-related. AI Anxiety may still exist, but its explanatory role may be attenuated when trust, usefulness, and control are

simultaneously included in the model, especially if these constructs already capture much of the positive–negative evaluation process surrounding AI use. A third explanation is contextual normalization: in higher education settings where generative AI has become embedded in routine academic practices, anxiety may no longer function as a major inhibitor of intention, particularly among respondents who already have direct experience with such tools. Therefore, the non-significant effect of AI Anxiety should be interpreted cautiously as a sample- and context-specific result rather than as evidence that anxiety is universally irrelevant in generative AI adoption.

The structural model reveals that generative AI adoption in higher education is driven by a combination of cognitive and affective mechanisms. While usability and usefulness remain important (as suggested by TAM), trust emerges as the most critical factor influencing behavioral intention. The integration of Interface Quality and Algorithmic Transparency into the model provides a more comprehensive understanding of Human–AI Interaction. Interface Quality primarily enhances usability, while Algorithmic Transparency strengthens control and trust. Together, these factors create a synergistic effect that shapes user perception and adoption behavior. These findings contribute to the literature by demonstrating that traditional technology acceptance models need to be extended with trust and transparency constructs to adequately explain generative AI adoption. In this context, AI systems are not merely tools but interactive agents, requiring users to evaluate not only their functionality but also their reliability, transparency, and controllability.

### **3.3.7. Theoretical Implications**

This study contributes to the literature by extending the Technology Acceptance Model (TAM) within the context of generative AI through the integration of Human–AI Interaction perspectives. The findings demonstrate that traditional cognitive factors such as Perceived Ease of Use and Perceived Usefulness remain relevant but are insufficient to fully explain user behavior in AI-driven environments. Instead, Trust in AI emerges as the most critical determinant of Behavioral Intention, highlighting the importance of affective and relational mechanisms in AI adoption.

Furthermore, the incorporation of Interface Quality and Algorithmic Transparency as higher-order constructs provides a more nuanced understanding of how system design

and explainability influence user perceptions. Interface Quality primarily enhances usability, while Algorithmic Transparency strengthens perceived control and trust. This dual-path mechanism confirms that generative AI adoption is shaped by both cognitive evaluation and psychological assurance, thereby advancing existing acceptance models toward a more interaction-centric framework. Additionally, the non-significant role of AI Anxiety suggests that, in contexts where users are already familiar with AI technologies, psychological barriers may diminish, indicating a shift in user behavior from resistance to normalization of AI use.

### **3.3.8. Practical Implications**

From a practical perspective, the findings suggest that developers and educational institutions should prioritize trust-building mechanisms in generative AI systems. Enhancing algorithmic transparency such as providing clear explanations, justifications, and communicating system limitations can significantly improve users' perceived control and trust. Moreover, improving interface quality remains essential to ensure ease of use and reduce cognitive burden, particularly for students who rely on AI tools for academic tasks. However, the relatively weaker direct effect of interface quality on perceived usefulness indicates that system functionality and output quality should also be carefully optimized. For higher education institutions, the results highlight the importance of integrating AI tools into learning environments in a way that promotes both usability and trust. Training programs and digital literacy initiatives can further support effective AI adoption by helping students understand how AI systems work and how to use them critically. The successful adoption of generative AI in education requires not only technically efficient systems but also transparent, trustworthy, and user-centered design approaches.

## **4. CONCLUSION**

This study examines generative AI adoption in higher education by integrating Technology Acceptance Model (TAM) constructs with Human-AI Interaction perspectives. The findings indicate that while cognitive factors such as Perceived Ease of Use and Perceived Usefulness remain significant, Trust in AI emerges as the main driver of Behavioral Intention and represents the strongest mechanism explaining users' willingness to adopt generative AI in higher education. This suggests that adoption

decisions are influenced not only by functional evaluations, but also by users' confidence in the reliability and dependability of AI systems. The results further show that Interface Quality and Algorithmic Transparency contribute through complementary pathways. Interface Quality primarily enhances usability perceptions, thereby supporting the cognitive pathway of adoption through ease of use and usefulness, whereas Algorithmic Transparency strengthens perceived control, usefulness, and trust, thereby supporting the affective and relational pathway of Human-AI Interaction. These findings support the view that successful generative AI adoption depends on both effective system design and trustworthy interaction mechanisms. AI Anxiety was not found to have a significant direct or moderating effect in this study. This result should be interpreted cautiously, as it may reflect the relatively experienced respondent profile and the increasing normalization of AI use in academic environments rather than the universal absence of anxiety effects. Thus, the non-significant role of AI Anxiety should not reduce the importance of psychological factors, but rather indicates that trust, usefulness, control, interface quality, and transparency were more decisive in the present empirical context. This study contributes to the literature by providing an integrated perspective that combines cognitive and affective drivers of generative AI adoption in higher education. The central contribution of this study is the demonstration that trust is the strongest determinant of behavioral intention, while interface quality and algorithmic transparency operate as complementary antecedents that shape adoption through usability, perceived usefulness, perceived control, and trust. However, several limitations should be acknowledged. First, the cross-sectional design limits causal inference over time. Second, the sample includes a mixed respondent composition of students, lecturers, and administrative staff, which may involve differing usage perspectives. Third, the study was conducted within the regional context of West Nusa Tenggara, Indonesia, which may limit broader generalizability. Future studies may employ longitudinal designs, compare respondent groups, and test the model across wider institutional and geographical settings

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