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Mapping the Ethical Journey of Continuance Intention to Use Generative AI among University Students

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Abstract: *This study empirically investigates the psycho-ethical mechanisms driving the continuance intention to use generative artificial intelligence (GenAI) among university students in Vietnam. Departing from dominant theories such as the technology acceptance model (TAM) or the unified theory of acceptance and use of technology (UTAUT), this research applies Rest's (1986) four-component model to suggest ethical factors influencing continuance intention to use GenAI. The study examines a sequential cognitive process from moral awareness (AI literacy and AI responsibility) through moral judgment (critical evaluation) to moral motivation (moral obligation and academic integrity) and its role in shaping continuance intention in using GenAI. Data collected from 448 university students were analyzed using partial least squares structural equation modeling (PLS-SEM). The results validate the sequential ethical decision-making process, identifying critical evaluation as a vital mediator between awareness and motivation. Furthermore, both critical evaluation and academic integrity affect the continuance intention directly and positively. Additionally, the findings reveal a significant negative impact of moral disengagement on AI responsibility, acting as a psychological barrier that disrupts the sustainable and ethical decision-making process. These insights provide a strategic foundation for educational institutions and policymakers to design interventions that foster ethical and sustainable GenAI adoption among university students.*

Keywords: continuance intention, generative artificial intelligence, moral disengagement, Rest's four-component model, university students.

I. Introduction

The emergence of new artificial intelligence (AI) technologies, particularly generative AI (GenAI) like ChatGPT, has had a profound impact on individuals, organizations, and society across many fields. For higher education, GenAI, with its ability to generate text, images, and programming code, is gradually becoming an integral part of the daily learning activities of students worldwide [1]. This tool is creating a revolutionary paradigm shift in how students interact with academic materials [2, 3]. The use of GenAI has a significant positive impact on student learning outcomes, such as improving students' academic writing skills [4-7], reducing cognitive burden and personalizing learning for students [6, 8, 9]. However, it also seriously challenges traditional standards of academic integrity and personal effort [10, 11]. Some studies show that reliance on and the unethical use of GenAI can negatively impact students' critical thinking skills [12], as well as their originality and creativity [5, 13].

Despite the negative aspects of GenAI, a complete prohibition is neither feasible nor sustainable. Conversely, the integration of this tool into students' learning processes should be encouraged [12]. This is not only because of the positive impacts that GenAI brings, but also because of the demand for training a high-quality workforce capable of adapting to digital technology and familiarizing themselves with the professional environment [14, 15]. On the other hand, some studies have shown that ethical factors, such as perceived ethics or ethical judgment, have a positive impact on promoting students' intention and behavior to use GenAI responsibly [15, 16]. By contrast, other studies suggest that using GenAI is like a form of cheating, so if users have high academic integrity, they will limit their use of GenAI [17]. This suggests that the effect of ethical factors on behavioral intention is significant and diverse depending on context. Therefore, this study argues that research on ethical factors across various social contexts is needed to promote ethical and sustainable use of GenAI by students.

Although GenAI is becoming increasingly popular, research related to the deep ethical mechanisms driving continued usage intentions remains limited [16, 18, 19]. Most current studies rely on mainstream functional models such as the TAM Model [20] or the UTAUT theory [21, 22] to explain user behavior. To further explore factors that influence behavioral intention in using an AI model among studies, some studies integrate the TAM or UTAUT model with other theories, such as TPB [3, 23], self-determination theory [24], or the value-based adoption model [25]. While these theoretical frameworks offer valuable insights into technical characteristics such as perceived usefulness and perceived ease of use, they often fail to fully capture the specific psychological nuances in the interaction between humans and technologies [26, 27]. Therefore, some studies have extended the TAM or UTAUT model to add ethical factors like perceived ethics [26] , ethical judgment [16], or academic integrity [28] to explain the ethical aspects in GenAI usage of university students. However, most of the literature only addresses ethics superficially as a monolithic concept, lacking a deep connection with established philosophical and psychological theories [19] while ethical and psychological factors do not operate independently but interact with each other in a complex way.

This study aims to fill this gap by using Rest's four-component model [29] to explore psychological- ethical factors driving Vietnamese students' intention to continue using GenAI. The originality of this study lies in two specific aspects. Firstly, this study suggests moral factors and their interaction by applying Rest's four-component model [29], a classical ethical theory that has rarely been applied in GenAI studies. This means that instead of treating ethics as a static factor, the study examines the relationship between ethical factors from moral awareness (AI literacy and AI responsibility), through moral judgement (critical evaluation), to moral motivation (moral obligation and academic integrity). Moreover, this study also investigates the impact of moral evaluation and moral motivation on continuance intention to use GenAI. This approach clarifies how ethical factors interact and transform into long-term behavioral intentions. Secondly, the study identifies and quantifies moral disengagement, a factor almost unstudied in research on the influence of this mechanism on the moral awareness stage, specifically the awareness of responsibility among students.

To achieve the above objective, the study addresses four main research questions (RQ):

- **RQ1**: Does critical evaluation mediate between moral awareness factors (AI literacy and AI responsibility) and moral motivation factors (moral obligation and academic integrity) following Rest's four-component model?
- **RQ2**: Do critical evaluation, moral obligation, and academic integrity affect continuance intention in using GenAI?
- **RQ3**: Does moral disengagement affect AI responsibility?

II. Literature review and hypotheses development

2.1 GenAI as a learning tool in higher education

Generative artificial intelligence (GenAI) is defined as a set of artificial intelligence technologies that can produce text, images, and other forms of content through the application of deep learning algorithms on large amounts of data [30]. While traditional AI systems work on the principle of rules and regulations, GenAI has the ability to create content through the application of deep learning techniques [31]. Recent studies highlight that GenAI tools could create content that resembles human language due to their contextual understanding capabilities [25, 32]. This technological shift represents a significant transformation from analytical and task-specific AI systems to content-generating systems with unprecedented flexibility and speed [33].

In higher education, GenAI has been increasingly adopted to support and enhance students' learning experiences. According to Kangwa, et al. [30], GenAI has the potential to provide personalized feedback to the student, which may lead to increased learning efficiency. In addition, GenAI has the potential to promote the critical thinking, problem-solving, and creative skills of the student through the provision of alternative perspectives and ideas during the learning experience [30]. Various studies have also revealed that Gen AI has the potential to assist the student with their writing through the provision of timely support and the improvement of the quality of the student's writing, especially for non-native English speakers [25, 31]. Beyond writing support, GenAI also contributes to academic research activities by summarizing complex information [31], generating research ideas [33], and accelerating scholarly work through drafting and synthesizing scientific texts [32].

Despite these benefits, the integration of GenAI in the learning environments raises substantial ethical and academic concerns. One major concern is plagiarism, whereby students may use the output of AI to present their work as their own, thereby compromising the authenticity and validity of academic work [31]. This problem is further complicated by the inability of existing plagiarism tools to identify AI-generated content from that written by humans [34]. Another major concern is the hallucination phenomenon, whereby AI may present false and misleading information that may sound true, including false information and false science [25, 32, 35]. Moreover, the overuse of GenAI may compromise the development of key academic skills such as independent critical thinking, problem-solving, and creativity [31]. From the psychological perspective, Wang [36] has noted AI-induced anxiety among students, which is attributed to the perceived threats of job displacement and feelings of inadequacy and competition with AI performance.

Taken together, the current research suggests that GenAI represents a significant opportunity and challenge from an ethical perspective. Moreover, the dual nature of GenAI suggests that it must be understood not simply as an aid to the student but rather as a technological phenomenon that affects the cognitive, ethical, and psychological experience of the student. Thus, to fully understand students' intentions and behaviors regarding GenAI, ethical perspectives are essential. It could explain how individuals recognize moral issues, make value-based judgments, and regulate their actions. Moral frameworks emphasize that GenAI use is not merely a technical decision but also a reflection of personal responsibility and adherence to ethical standards. Therefore, students' engagement with generative AI should be examined through the lens of ethical reasoning and moral commitment in addition to practical considerations.

2.2 Continuance intention to use GenAI

Continuance intention refers to an individual's conscious plan to keep using a technology after initial adoption, based on prior experience and evaluation [37]. In the context of GenAI, this concept is particularly important because the technology has already become embedded in students' academic practices. Thus, research attention should move beyond initial acceptance toward understanding whether students intend to sustain GenAI use in the future.

In prior studies, behavioral intention has long been recognized as the strongest predictor of actual technology use. Parveen, et al. [38] define behavioral intention as the subjective probability that an individual will engage in a specific behavior, while Choung, et al. [39] emphasizes its role as an indicator of willingness to adopt and integrate technology. Empirical studies applying TAM, TPB, and UTAUT2 consistently demonstrate that perceived usefulness, perceived ease of use, and attitudes toward GenAI significantly predict students' intention to use it for academic tasks such as writing, idea generation, and information retrieval [25, 30, 32, 35].

However, continuance intention reflects more than functional acceptance. It captures students' overall evaluation of their prior experiences, including satisfaction and perceived value [40, 41]. Yu, et al. [42] show that GenAI's ability to provide relevant information and problem-solving support strengthens students' motivation to continue using the technology. At the same time, ethical and integrity-related concerns act as critical boundary conditions. Fear of plagiarism and perceived risks related to privacy and data security negatively influence intention to use GenAI [25]. Moreover, academic integrity functions as a key moderating factor between intention and actual use [32]. Taken together, continuance intention to use GenAI represents a balance between perceived usefulness and ethical acceptability. Understanding this balance is essential for explaining how GenAI can be sustainably integrated into higher education in a responsible manner.

2.3 Theoretical framework

Rest's four-component model

To overcome the limitations of existing approaches, this study adopts Rest's four-component model as its primary theoretical framework [29]. According to this model, moral action involves four interrelated stages: moral awareness, moral judgment, moral motivation, and moral behavior. Moral awareness refers to an individual's ability to perceive that a situation contains ethical issues. Moral judgment involves evaluating which action is morally right or wrong based on moral principles and standards. Moral motivation reflects the extent to which moral values are prioritized over competing interests such as personal benefit or convenience. Finally, moral behavior represents the actual execution of ethically guided decisions in practice. This model emphasizes that ethical action does not arise from a single factor but from the interaction between cognitive awareness, evaluative reasoning, motivational commitment, and behavioral enactment.

Rest's model is especially applicable to GenAI-assisted learning because learners are presented with morally ambiguous scenarios where technology plays an active role in content creation. Unlike traditional learning aids, GenAI systems disrupt long-held beliefs about authorship and accountability, therefore making technology use a moral decision rather than a technical decision.

Moral disengagement theory

In addition to Rest's model, the moral disengagement theory helps to explain how people justify their own violation of norms without feeling any guilt or self-blame [43]. Moral disengagement involves processes like displacement of responsibility, consequence minimization, and blame externalization. In GenAI learning, learners tend to blame the technology system for the inaccuracy or unethicality of the results rather than their own choice, thus undermining personal responsibility [44].

The integration of Rest's model and moral disengagement provides a comprehensive explanation of how continuance intention emerges from both reflective and justificatory processes. Moral awareness and judgment guide ethical evaluation, while moral disengagement enables students to bypass self-censure when moral standards conflict with perceived learning benefits.

Accordingly, this study conceptualizes continuance intention toward GenAI as a form of moral behavior shaped by ethical cognition and rationalization mechanisms. Moral awareness influences moral judgment, moral judgment shapes moral motivation, and moral motivation determines behavioral intention. At the same time, moral disengagement is expected to weaken these relationships by allowing students to sustain GenAI use despite ethical concerns.

Through this framework, continuance intention of GenAI usage is reconceptualized as a morally embedded learning practice rather than a value-neutral technological activity. This theoretical approach extends existing research by situating continuance intention within a structured ethical model and by highlighting the psychological mechanisms that govern responsible GenAI use in higher education. These theories together displayed a consolidated model for students' continuance intention to use GenAI for studying, by encompassing several determinants like AI literacy, AI responsibility, critical evaluation, moral obligation, and academic integrity (Figures 1 and 2).

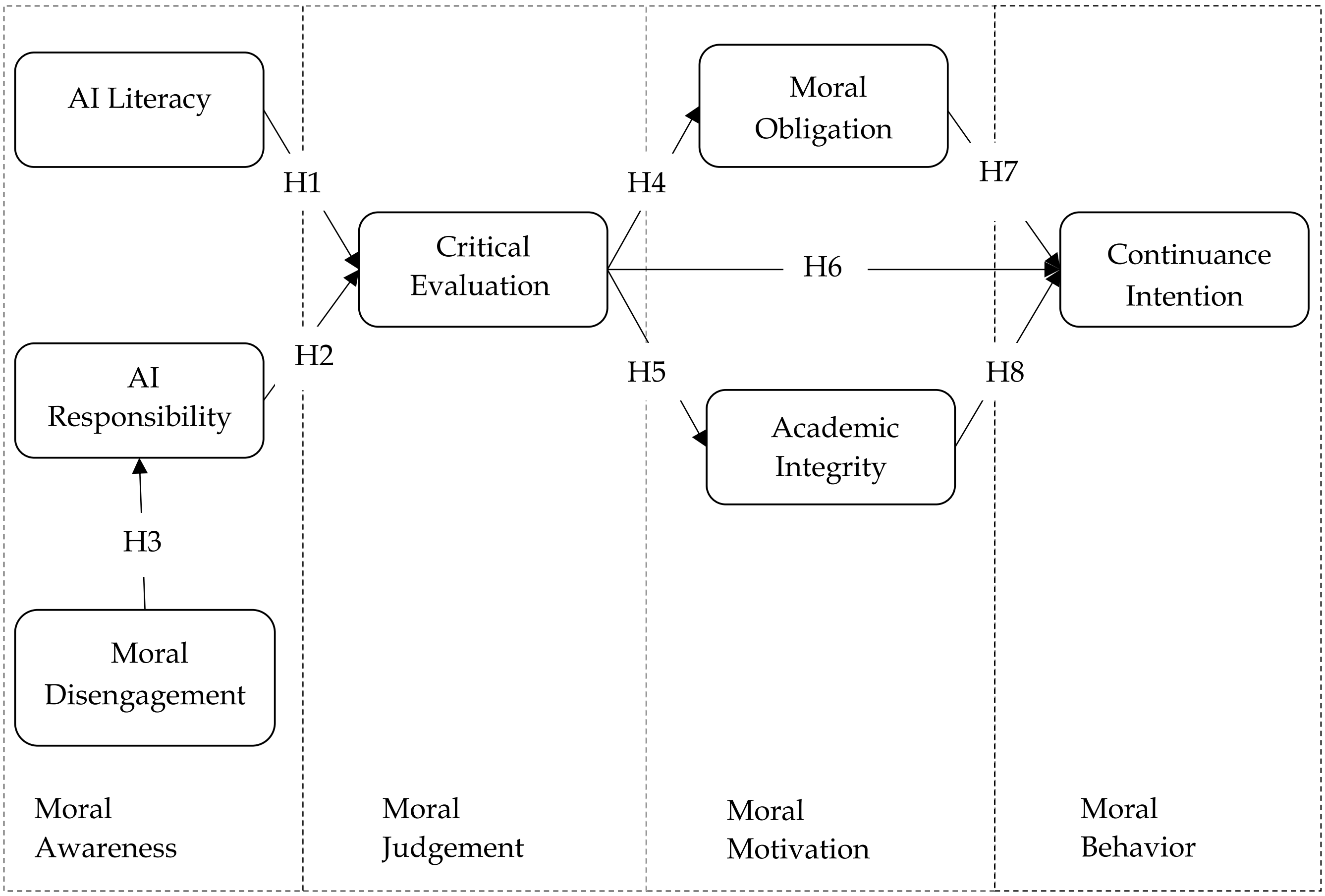

Fig 1. Conceptual Mode

2.3 Hypotheses development

Phase 1: Moral awareness

AI Literacy

In Rest's four-component model, moral awareness refers to the ability to recognize that a situation involves ethical issues and potential moral consequences. AI literacy gives people cognitive knowledge that allows them to realize the way AI systems function and where there can be ethical problems, thus increasing their awareness about the ethical problems that can arise in AI use. AI literacy is defined as the ability to critically understand and evaluate AI systems and their outputs, going beyond technical proficiency to encompass ethical and social knowledge [45-47]. Specifically, this enables user to critically assess whether the AI output is consistent with moral values and cultural norms [48, 49]. Following Rest's (1986) four-component model, moral judgment happens after the recognition that a moral dilemma exists. Hence, AI literacy has a cognitive basis for critical assessment of AI outputs [50, 51]. Empirical evidence also shows that the more objective and responsible judgments of AI-related situations are made by users with higher levels of AI literacy [52, 53]. Therefore, we propose the following hypothesis:

H1: AI literacy has a positive impact on the critical evaluation.

AI responsibility

According to Rest [29] four-component model, moral awareness refers to the fact that not only can people understand the situation, but also comprehend their accountability in that situation in order to be aware of the consequences of the action. In AI-related applications, AI responsibility not only involves technical knowledge but also a sense of commitment to make sure that decisions and actions are consistent with ethical values and social norms [54]. Moreover, ethical AI guidelines highlight responsibility as the basis for actively dealing with moral problems instead of assigning them to technology [55]. Empirical evidence indicates that students who feel a greater sense of responsibility for AI use are more likely to critically assess the fairness, accuracy, and social implications of AI-generated outputs [3]. Thus, we propose the following hypothesis:

H2: AI responsibility use positively influences the critical evaluation.

Moral disengagement

Moral disengagement is the cognitive process of separating one's standards of behavior from actual behavior, which enables people to engage in misconduct without punishing themselves [43]. This theory suggests that moral disengagement could directly affect moral awareness, which is weakened by the lack of recognition of misconduct. In the context of GenAI use, students tend to blame external pressures or the technology itself for misuse, considering it a technical requirement rather than misconduct. Empirical research has shown that moral disengagement is positively related to a lack of sensitivity to integrity risks and a lack of feelings of guilt in using AI [56, 57]. Hence, we propose the following hypothesis:

H3: Moral disengagement negatively influences AI responsibility.

Phase 2: Moral Judgment

Critical evaluation

In Rest's four-component model, critical evaluation corresponds to moral judgment, which then activates moral motivation. Therefore, as moral obligation represents an internal sense of duty to act according to ethical principles, it presents itself once moral judgment has been formed [58]. Drawing on the concept of moral obligation, awareness of consequences, and personal responsibility gives rise to a felt duty to act ethically. Empirical research suggests that fostering critical reflection on AI outputs enhances students' sense of responsible and ethical AI use [59-61]. Therefore, we propose the following hypothesis:

H4: Critical evaluation positively influences moral obligation

Similarly, academic integrity is defined as honesty, responsibility, and fairness in knowledge creation and use [7]. As academic integrity represents moral motivation, it is also reinforced through critical evaluation. Previous studies have shown that ethical instruction and critical thinking about AI promote autonomous thinking and academic integrity [13, 59, 62, 63]. Hence, we propose the following hypothesis:

H5: Critical evaluation positively influences academic integrity

Beyond affecting moral motivation, critical evaluation could also directly impact continuance intention to use GenAI. Continuance intention to use GenAI represents users' intention to continue using GenAI in the future based on their past experiences, satisfaction, and cognitive evaluation of the technology [23]. Based on Rest's moral development theory, critical evaluation of AI is associated with moral awareness and moral judgment, which serve as the foundation for the motivation to participate in moral and sustainable behavior. In some studies, critical evaluation is associated with increased perceived control and rational decision-making, which in turn strengthens behavioral intention. Empirical evidence shows that users with higher critical and ethical judgment demonstrate more sTABLE trust and continuance intention towards GenAI [16, 64, 65]. Therefore, we propose the following hypothesis:

H6: Critical evaluation positively influences students' continuance intention to use GenAI

Phase 3: Moral Motivation

Moral Obligation

Moral obligation is the internalization of personal values and conscience, rather than external pressure or instrumental gain [66]. Moral obligation could represent the moral motivation in Rest's four-component model, which is the process of transforming ethical beliefs into specific behavioral intentions. In GenAI, the belief that responsible use is a moral obligation [58, 67]. There is also empirical evidence that moral obligation is a strong predictor of behavioral intention in general [66]. Moral obligation may thus be a positive predictor of students' intention to continue using GenAI for good learning purposes [15, 36]. Thus, we propose the following hypothesis:

H7: Moral obligation positively influences students' continuance intention to use GenAI.

Academic integrity

Academic integrity represents core values of honesty, responsibility, and respect that guide students' engagement with emerging technologies such as GenAI [7, 17]. Rest [29] provides a key theoretical foundation for explaining the mechanisms underlying academic integrity. In the stage of moral motivation, individuals prioritize moral values over competing interests based on their concern for personal integrity and voluntary adherence to ethical principles. Accordingly, academic integrity can be viewed as a core motivational driver of students' ethical behavior in learning contexts. The development of academic integrity thus reinforces responsible and sustainable patterns of GenAI use, motivating students to continue using GenAI for academic purposes without violating ethical norms. This model further suggests that integrity-oriented students form ethical intentions that support responsible and sustainable behavior. Empirical findings indicate that positive academic integrity of GenAI enhances students' continuance intention [17, 23]. Therefore, we propose the following hypothesis:

H8: Academic integrity positively influences students' continuance intention to use GenAI.

III. Methodology

3.1. Research design and data collection

This study adopts a quantitative research approach to examine the factors influencing students' continuance intention to use Generative AI (GenAI) in their learning. The research process begins with a preliminary literature review to identify research gaps, formulate questions, and establish objectives. Following the identification of key ethical factors, a conceptual model and hypotheses were developed based on Rest's four-component model and prior literature. The research employed a cross-sectional design with an online survey distributed to Vietnamese university students.

The questionnaire was developed through a multi-stage process. First, through a literature review, we selected the suitable scales for the variables that were decided and chose the most suitable for each. Then, we conducted qualitative pretesting with 20 students to assess clarity and relevance, and a pilot quantitative survey with 50 students to evaluate preliminary reliability. The final survey was administered via Google Forms through social media platforms, including Facebook, Zalo, and student forums, yielding 578 responses. After data cleaning to remove invalid responses, 448 usable responses were retained for final analysis.

3.2. Measurements

All constructs were measured using five-point likert scales ranging from 1 (strongly disagree) to 5 (strongly agree). The measurement items were adapted from previously validated scales and contextualized for GenAI usage in academic settings. AI responsibility (AR) was measured using three items from Consoli and Petko [61]. AI literacy (AL) was assessed through nine items developed by Koch, et al. [68]. Critical evaluation (ACE) of GenAI employed four items from Wang [36]. Academic integrity (AIN) was measured using seven items adapted from Mohamed Eldakar, et al. [7]. Moral obligations (MO) were assessed using three items from Cronan, et al. [58]. Continuance intention (CI) to use GenAI was measured with three items from Zhang, et al. [69]. Finally, moral disengagement (MD) was captured using six items from Zhang, et al. [70]. The questionnaire also included demographic questions on gender, academic year, field of study, and frequency of GenAI usage.

3.3. Sampling and data analysis

The target population comprised Vietnamese university students who actively use GenAI for learning purposes. Due to time and resource constraints, a non-probability convenience sampling method was employed. This study targeted 580 responses and used 448 responses. Data analysis employed SPSS version 22 for descriptive statistics and SmartPLS version 4.1.1.7 for structural equation modeling. PLS-SEM was selected due to its suitability for prediction-oriented research and its capacity to handle complex models with multiple constructs [71].

For data analysis, the analysis followed a two-stage approach: measurement model evaluation and structural model assessment. Measurement model evaluation assessed indicator reliability through outer loadings, internal consistency via composite reliability (CR), convergent validity through average variance extracted (AVE), and discriminant validity using the Fornell-Larcker criterion and HTMT ratio. Structural model assessment examined path coefficient significance through bootstrapping with 5,000 subsamples, explanatory power via R^2, predictive relevance through Q^2, and effect sizes using f^2 [72].

IV. Results

4.1. Sample profile

The demographic characteristics of the participants are presented in TABLE 1. The sample included 22.5% males and 76.6% females, predominantly third-year and fourth-year students from non-STEM majors; 81,7% of participants are using GenAI every day.

TABLE 1: Participants' demographics

Gender	**Frequency**	**Percent**
Male	101	22.5
Female	343	76.6
Others	4	9
School year		
1st	28	6.3
2nd	98	21.9
3rd	212	47.3
4th	110	24.6
Major group		
STEM	85	19
Non-STEM	363	81

Frequency of GenAI usage		
Rarely (once a month or less)	16	3.6
Occasionally (1–3 times per week)	66	14.7
Frequently (once a day or several times per week)	194	43.3
Always (two or more times per day)	172	38.4

4.2. Measurement model

The present study evaluated the measurement model by examining the reliability and validity of the constructs. The assessment focused on key criteria, including indicator reliability (outer loadings), internal consistency reliability, and both convergent and discriminant validity.

According to Hair [71], factor loadings (outer loadings) exceeding 0.70 are considered adequate to establish reliability and validity; indicators with loadings below 0.40 should be eliminated from the model. However, if the composite reliability (CR) and average variance extracted (AVE) meet the recommended thresholds, indicators with loadings between 0.40 and 0.70 may be retained if they are deemed theoretically significant to the study. In this research, item AL5, which exhibited an outer loading of 0.278, was removed from the initial pool of 35 survey items.

Christian M. Ringle [73] posit that a scale achieves convergent validity if the AVE reaches at least 0.50. This 0.50 (50%) threshold signifies that, on average, the latent construct explains at least 50% of the variance of its respective indicators. Upon observing that the AVE for the AI literacy (AL) construct was 0.452, we proceeded to exclude the two items with the lowest outer loadings, AL4 and AL5, to increase the AVE index to 0.516 (TABLE 2). Furthermore, according to Hair and Alamer [74], The research team needs to combine cronbach's alpha with a composite reliability coefficient analysis. Thus, based on TABLE 2, the composite reliability values of the scales range from 0.7 to 0.9, indicating that these scales are all highly reliable.

TABLE 2: Measurement model results

Construct	Item	Loading	Cronbach's alpha	Composite reliability (CR)	AVE
ACE	ACE1	0.796	0.780	0.857	0.601
	ACE2	0.743			
	ACE3	0.782			
	ACE4	0.778			
AIN	AIN1	0.664	0.835	0.876	0.504
	AIN2	0.733			

	AIN3	0.776			
	AIN4	0.593			
	AIN5	0.735			
	AIN6	0.725			
	AIN7	0.728			
AL	AL1	0.722	0.844	0.882	0.516
	AL2	0.745			
	AL3	0.706			
	AL6	0.718			
	AL7	0.697			
	AL8	0.734			
	AL9	0.707			
AR	AR1	0.849	0.734	0.848	0.650
	AR2	0.814			
	AR3	0.754			
CI	CI1	0.925	0.862	0.916	0.784
	CI2	0.925			
	CI3	0.801			
MD	MD1	0.819	0.907	0.926	0.678
	MD2	0.723			

	MD3	0.901			
	MD4	0.889			
	MD5	0.796			
	MD6	0.801			
MO	MO1	0.789	0.789	0.875	0.700
	MO2	0.855			
	MO3	0.864			

Discriminant validity - a critical component of measurement model assessment - was examined using the Larcker [75] criterion. The results indicate that the square root of the AVE for each latent construct was greater than its correlation coefficients with all other constructs (TABLE 3). This confirms that each latent variable measures a distinct concept and does not correlate excessively with other factors, thereby establishing discriminant validity. Additionally, discriminant validity was assessed via the heterotrait–monotrait (HTMT) ratio, which measures the correlation between variables of different constructs. The results in TABLE 3 show that all HTMT ratios were below the conservative threshold of 0.85 or 0.90 [76], satisfying the requirements for construct independence. In TABLE 3, no factor index is above 0.9, so all factors are distinct and do not have overlapping significance.

TABLE 3: Discriminant Validity of the reflective scale

Heterotrait-monotrait ratio (HTMT)

	ACE	AIN	AL	AR	CI	MD	MO
ACE							
AIN	0.781						
AL	0.738	0.643					
AR	0.560	0.666	0.517				
CI	0.501	0.467	0.349	0.454			
MD	0.142	0.231	0.095	0.310	0.127		
MO	0.464	0.580	0.371	0.427	0.225	0.366	

Fornell-Larcker criterion

	ACE	AIN	AL	AR	CI	MD	MO
ACE	0.775						
AIN	0.639	0.710					

AL	0.604	0.542	0.719				
AR	0.433	0.530	0.411	0.807			
CI	0.424	0.418	0.296	0.374	0.886		
MD	-0.120	-0.226	-0.033	-0.281	-0.131	0.824	
MO	0.374	0.475	0.305	0.327	0.207	-0.338	0.837

4.3. Structural model

The evaluation involves determining the significance of the hypothesized relationships, measuring the explained variance (R2), evaluating the model's predictive relevance (Q2), and determining the effect size (f2). To test the reliability of the estimates, the study used the bootstrapping technique with 5000 iterations.

The structural model evaluation involves determining the significance of the hypothesized relationships, measuring the explained variance (R2), evaluating the model's predictive relevance (Q2), and determining the effect size (f2). To test the reliability of the estimates, the study used the bootstrapping technique with N = 5000 draws.

The results in TABLE 4 of the bootstrapped path coefficients show that at the moral awareness phase, AI literacy ($\beta = 0.513$, $p = 0.000$), AI reliability ($\beta = 0.223$, $p= 0.000$), positively influence critical evaluation and moral disengagement ($\beta = -0.281$, $p = 0.000$), and negatively impact AI responsibility. Hypotheses H1, H2, and H3 are supported. Similarly, at the moral judgement phase, H4 is accepted as critical evaluation ($\beta = 0.374$, $p = 0.000$) affects moral obligation positively, and the same with H5 when critical evaluation ($\beta = 0.639$, $p = 0.000$) impacts academic integrity positively. For the continuance intention, while critical evaluation ($\beta = 0.267$, $p = 0.000$) and academic integrity ($\beta = 0.254$, $p = 0.000$) are positively significant, Moral obligation ($\beta = -0.013$, $p = 0.804$) is non-significant. Therefore, H7 and H8 are supported, but H6 is not supported.

R^2 and adjusted R^2 reflect the extent to which the independent variables in the model can explain the variation of each dependent variable. The results from TABLE 4 and Figure 2 show that AI literacy and AI reliability explain 40.6% of the variation in critical evaluation ($R^2 = 0.406$), indicating a good level of explanation. Similarly, critical evaluation explains 40.9% of the variation in academic integrity ($R^2 = 0.409$), showing the important role of critical thinking. For continuance intention, the variables critical evaluation, academic integrity, and moral obligation explain 21.6% of the variation ($R^2 = 0.216$), reaching a medium level of explanation. Meanwhile, moral obligation ($R^2 = 0.140$) has low levels of explanation, suggesting they may still be influenced by factors outside the model.

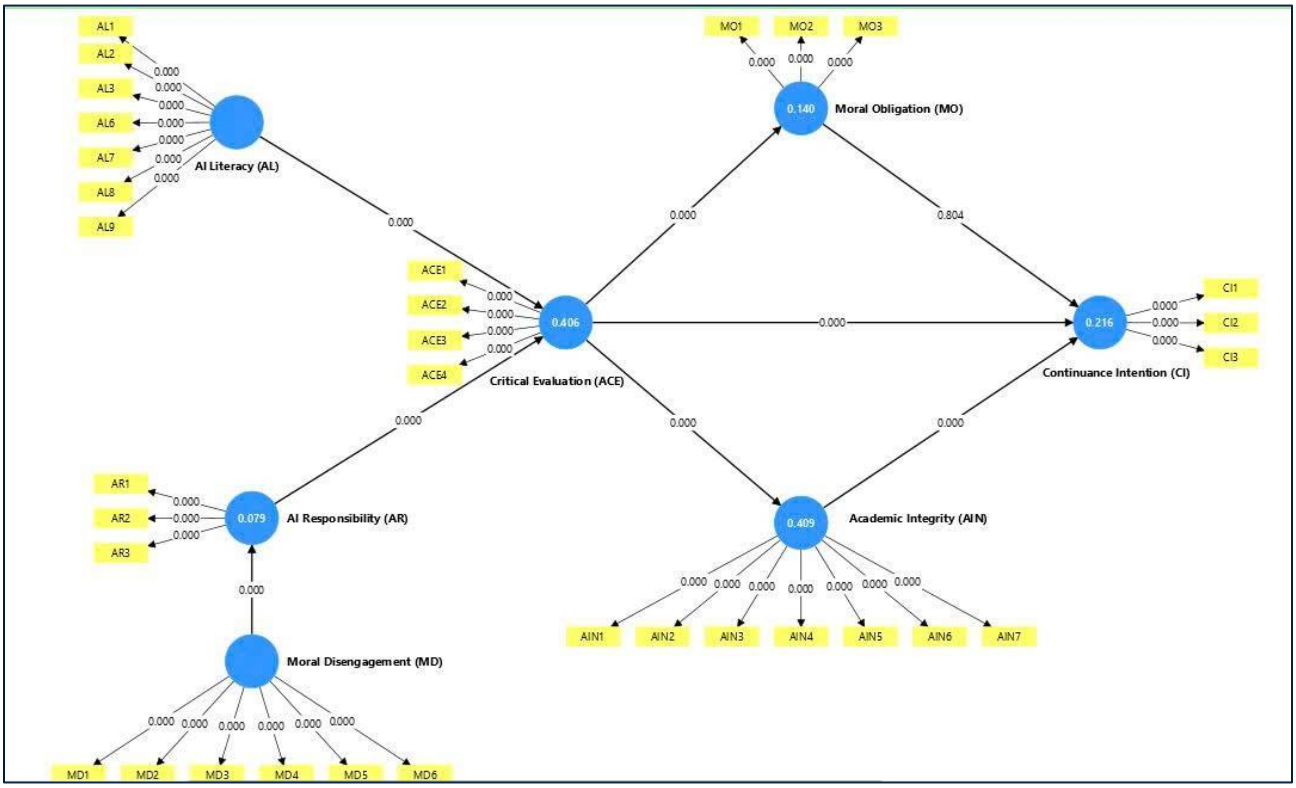

Fig 2: PLS Algorithm using SmartPLS

TABLE 4: Path coefficients in the structural model and the results of the significance tests

Hypothesis	Path	β	t-statistics	f^2	p-values	Decision
H1	AL -> ACE	0.513	13.127	0.368	0.000	Supported
H2	AR -> ACE	0.223	4.962	0.070	0.000	Supported
H3	MD -> AR	-0.281	6.073	0.086	0.000	Supported
H4	ACE -> MO	0.374	7.541	0.162	0.000	Supported
H5	ACE -> AIN	0.639	16.271	0.691	0.000	Supported
H6	ACE -> CI	0.267	4.060	0.053	0.000	Supported
H7	MO -> CI	-0.013	0.248	0.000	0.804	Not Supported
H8	AIN -> CI	0.254	3.516	0.043	0.000	Supported

The results above indicate that the research model has a moderate to good explanatory power for the dependent variables. However, to further assess the extent of the influence of each independent variable on the corresponding dependent variable, the study continues to use the effect size index f^2 in TABLE 4. The f^2 results show that the impacts of critical evaluation on academic integrity (0.691) and AI literacy on critical evaluation (0.368) have a large impact, confirming the key role of critical evaluation and AI literacy. The critical evaluation and moral obligation (0.162) relationships have a medium impact, while the impact of moral disengagement on AI responsibility (0.086) and AI responsibility on critical evaluation (0.070) have a small impact. For continuance intention, critical evaluation, and academic integrity, have only small impacts, while moral obligation (0.000) has almost no contribution, consistent with the rejection of H6.

According to Shmueli, et al. [77], the forecasting capability assessment process includes two main steps: (1) Checking the Q^2 predictive values of the observed variables belonging to the endogenous structures, and (2) Comparing the forecast error of the PLS-SEM model with the linear model. In the first step, the result shows in TABLE 5 that all dependent variables (AR, ACE, AIN, MO, CI) have Q^2 predict values that are greater than 0 (0.070, 0.362, 0.260, 0.092, 0.084). This confirms that the research model has a predictive fit.

TABLE 5: Explanatory power evaluation and predictive relevance of constructs

Construct	R^2	R^2 *adjusted*	Q^2
Critical evaluation (ACE)	0.406	0.404	0.362
Academic integrity (AIN)	0.409	0.407	0.260
AI responsibility (AR)	0.079	0.077	0.070
Continuance Intention (CI)	0.216	0.211	0.084
Moral obligation (MO)	0.140	0.138	0.092

This study also suggests the critical evaluation as the mediator between Moral awareness factors (AI Literacy, AI responsibility) and moral motivation (moral obligation, academic integrity); it validates Rest's four-component model in the digital context. The results of these paths' indirect effects are shown in TABLE 6

TABLE 6: Specific indirect effects

Path	**β**	**t-statistics**	**p-value**
AL -> ACE -> AIN	0.328	8.938	0.000
AR -> ACE -> AIN	0.143	4.380	0.000
AL -> ACE -> MO	0.192	6.260	0.000
AR -> ACE -> MO	0.083	3.697	0.000

V. Discussion

This study develops and empirically validates an integrated theoretical framework combining Rest's four-component model [29] with Bandura's moral disengagement theory [43] to explain Vietnamese students' continued intention to use generative artificial intelligence (GenAI) in higher education. The findings provide robust support for most hypothesised relationships and offer nuanced insights into how cognitive, moral, and behavioural mechanisms interact within digitally academic environments. To clarify the underlying psychological mechanism, the proposed model is structured into three sequential phases:

5.1. Moral awareness

Moral awareness emerges when students recognise that GenAI usage carries ethical implications beyond technical functionality. In this stage, AI literacy and AI responsibility enhance ethical sensitivity, whereas moral disengagement weakens it. AI literacy (AL) emerges as the most influential antecedent of critical evaluation, with a substantial positive effect (β = 0.513, p = 0.000). This strong association underscores the foundational role of technological understanding in stimulating ethical awareness and reflective judgment. Students who comprehend the operational logic, data dependencies, and inherent limitations of AI systems are more inclined to scrutinise outputs critically rather than accept them at face value. In this respect, the results reinforce the argument advanced by Long and Magerko [47] that technological competence is a prerequisite for recognising broader societal and ethical risks. Within the Vietnamese educational context, AI literacy appears to transform GenAI usage from a purely instrumental activity into a reflective process embedded with epistemic responsibility and moral consideration.

In addition to literacy, AI responsibility (AR) also demonstrates a significant positive effect on critical evaluation (β = 0.223, p = 0.000). When students perceive themselves as accounTABLE for the academic and intellectual consequences of GenAI usage, they engage in deeper moral reasoning. Rather than treating AI outputs as neutral tools detached from personal agency, students with heightened responsibility are more likely to deliberate on issues such as authorship, fairness, and academic honesty. This mechanism resonates with the ethical framework articulated by Floridi, et al. [78], who emphasise responsibility as a catalyst for self-regulatory moral assessment. The present findings suggest that responsibility functions as a psychological bridge connecting situational awareness to substantive moral judgment in AI-assisted learning.

Significantly, moral disengagement (MD) exerts a significant negative influence on AI responsibility (β = -0.281, p = 0.000). This result aligns closely with the conceptualisation of [43] of disengagement as a cognitive strategy that neutralises internal moral standards. By attributing agency to the machine or minimising personal involvement in content generation, students effectively attenuate their sense of obligation. The perception that the system generated the output can diminish ownership and weaken ethical self-regulation, thereby creating normative blind spots. Such dynamics mirror the observations of Zhang, et al. [70], who highlight how low detectability in digital environments may amplify disengagement tendencies. The present study extends this insight by demonstrating empirically how disengagement undermines responsibility in the specific context of GenAI adoption.

5.2. Moral judgment

Moral judgment functions as a reflective filter that translates awareness into evaluative conclusions. Critical evaluation (ACE) plays a central role in this stage. Critical evaluation further exerts a meaningful positive effect on moral obligation (MO) (β = 0.374, p = 0.000). Sustained engagement in evaluative thinking appears to facilitate the development of internalised ethical commitments. Students who habitually question AI outputs and reflect on potential biases or inaccuracies are more likely to articulate a personal sense of duty toward responsible use. This outcome is consistent with the argument advanced by Ngo and Hastie [60], who suggest that reflective competence strengthens confidence in navigating AI ethically and mitigates exposure to culturally or contextually biased content. The findings thus position critical evaluation as a central mechanism in cultivating normative awareness.

The impact of critical evaluation on academic integrity (AIN) is particularly pronounced (β = 0.639, p = 0.000), representing the strongest path within the structural model. In an academic landscape where AI-generated text challenges traditional plagiarism detection systems, internalised ethical scrutiny assumes heightened importance. Students who actively assess and refine AI outputs are more inclined to preserve transparency and intellectual ownership. This observation supports the pedagogical recommendations proposed by Pallant, et al. [8] and Prosper Setsoafia [59], who advocate for instructional approaches that encourage students to critically interrogate and responsibly integrate AI contributions rather than prohibiting their use outright. Integrity, in this sense, evolves from a restrictive principle into a collaborative ethic governing human–machine interaction.

Beyond its indirect effects through moral constructs, critical evaluation directly enhances continued intention to use GenAI (CI) (β = 0.267, p = 0.000). The ability to evaluate outputs effectively appears to cultivate what may be described as digital self-assurance. Students who feel competent in identifying inaccuracies or biases are less likely to perceive GenAI as a threat to academic standards and more likely to view it as a controllable, value-adding tool. This interpretation aligns with the perspective offered by Consoli and Petko [61], who contend that evaluative capacity fosters sustainable engagement with AI technologies.

5.3. Moral motivation

Moral motivation explains whether ethical orientations translate into continued behavioural intention. Interestingly, moral obligation (MO) does not significantly predict continued intention (β = -0.013, p = 0.804). Although students may acknowledge normative duties associated with AI use, such sentiments alone do not appear to drive sustained behavioural intention. This finding suggests that GenAI adoption among Vietnamese students is shaped more strongly by instrumental and competence-related considerations than by abstract moral imperatives. The result echoes the complexity highlighted by Cronan, et al. [58], who observes that ethical norms in digital contexts may lack the coercive clarity necessary to influence behavioural continuity directly.

In contrast, academic integrity (AIN) exerts a positive and statistically significant influence on continued intention (β = 0.254, p = 0.000). Rather than constraining usage, integrity functions as an enabling condition. Students who perceive themselves as capable of maintaining transparency and accountability in AI-assisted work demonstrate greater willingness to sustain usage. This supports the contention advanced by Maheshwari [23] that integrity can convert ethical reflection into confident technological engagement. When GenAI use is embedded within a framework of responsibility and openness, concerns about misconduct diminish, and continued adoption becomes more viable.

Collectively, the staged framework demonstrates that AI literacy and perceived responsibility stimulate critical evaluation, whereas moral disengagement undermines perceived responsibility. In turn, critical evaluation strengthens both moral obligation and academic integrity within the context of GenAI use. Ultimately, sustained intention to use GenAI is driven primarily by evaluative competence and academic integrity rather than moral obligation alone. These findings underscore the centrality of reflective competence and internalised ethical standards in shaping sustainable GenAI adoption.

VI. Conclusion

This study aims to fill the gap of prior researches those have not constructed the psychological-ethical mechanism which explain for continuance intention to use GenAI among university students. By applying Rest's four-component model, this study validates the mediating role of critical evaluation between moral awareness, including AI literacy, AI responsibility, and moral motivation, including moral obligation, and academic integrity. The results also reveal the role of critical evaluation and academic integrity in shaping continuance intention to use GenAI. Moreover, in the moral awareness stage, this study explores the negative relationship between moral disengagement and AI responsibility. Based on these theoretical findings, we not only contribute to studies related to ethical behavior in the digital education context but also make implications for higher educational institutions, lecturers, and students in order to enhance ethical and sustainable GenAI adoption.

6.1. Theoretical implications

This study advances the discourse on ethical artificial intelligence adoption in higher education through several theoretical contributions. First, it integrates the cognitive components of Rest's four-component model, including moral awareness, moral judgment, and moral motivation, with the psychological mechanisms of moral disengagement (Bandura, 1991). Rather than treating ethical behaviour as a linear process, the findings demonstrate that students' continuance intention toward generative AI emerges from a dynamic interaction between reflective cognition and psychological disengagement mechanisms.

Second, this study extends beyond traditional technology acceptance models, including the technology acceptance model [79] and the unified theory of acceptance and use of technology [80], which predominantly emphasise perceived usefulness and ease of use as predictors of behavioural intention. By employing Rest's moral decision-making framework as the theoretical foundation, this research positions critical evaluation as a mediator, highlighting the necessity of reflective filtering in transforming artificial intelligence literacy into sustainable behavioural intention. Within this framework, digital competence constitutes a necessary but insufficient condition for ethical technology adoption; it requires augmentation through evaluative skepticism and moral reasoning.

Third, the identification of moral disengagement as a significant psychological barrier extends research examining adverse digital behaviours. When students diffuse responsibility to artificial intelligence systems, they attenuate personal accountability, disrupting moral awareness and undermining responsible continuance.

6.2. Practical implications

For higher education institutions, the findings necessitate curricula integrating ethical considerations alongside technical training. Beyond prompt engineering workshops, institutions should incorporate artificial intelligence ethics case studies examining real-world dilemmas and reflective discussions addressing moral disengagement mechanisms. For example, institutions could develop structured exercises where students articulate personal accountability boundaries when using generative artificial intelligence.

For curriculum designers, assessment strategies should explicitly reward verification behaviours and transparent acknowledgment of artificial intelligence assistance. Assessment rubrics could include criteria evaluating students' capacity to critically evaluate artificial intelligence-generated content and document verification processes. Rather than implementing prohibitive policies that encourage concealment, institutions should normalise responsible collaboration under clearly articulated guidelines.

For students, systematic verification protocols constitute the primary mechanism for maintaining academic integrity. Students should cross-reference artificial intelligence outputs with peer-reviewed sources and maintain reflective journals documenting evaluative processes. Sustainable usage emerges from disciplined engagement wherein artificial intelligence functions as a cognitive partner subject to scrutiny and correction.

6.3. Limitations and directions for future studies

This study presents several limitations. First, reliance on self-reported data raises concerns regarding social desirability bias in measuring moral disengagement and academic integrity. Future research should incorporate behavioural experiments or longitudinal designs capturing actual responsible usage. Second, the explanatory power for the intention to continue using GenAI is not yet robust; future studies could fully integrate ethical factors with cognitive factors and technological acceptance to strengthen and refine the model of influencing factors for intention and behavior in using GenAI. Third, the study focuses on continuance intention rather than observable behaviour. Subsequent research could design and examine actual responsible usage and explore how moral cognition evolves as regulatory frameworks advance.

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