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FROM ADOPTION TO ACHIEVEMENT: THE ROLE OF AI LITERACY AND ACADEMIC INTEGRITY IN GENERATIVE AI USE AMONG INDONESIAN UNIVERSITY STUDENTS

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Abstract

Generative Artificial Intelligence (GenAI) is transforming higher education by enabling advanced automation and cognitive support; however, its educational and ethical impacts remain underexplored in developing contexts. This study investigates how GenAI use affects students' academic performance in Indonesian universities through an *Extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)* model that integrates *AI Literacy* and *Academic Integrity* as ethical-cognitive dimensions. Using survey data from 1589 students analyzed via Partial Least Squares structural equation modeling (PLS-SEM), the model explained 63.7% of the variance in *Behavioral Intention*, 75.1% in *Use Behavior*, and 78.8% in *Academic Performance*.

The results revealed that *Performance Expectancy* ($\beta = 0.294$, $p < 0.001$) and *Social Influence* ($\beta = 0.508$, $p < 0.001$) significantly drive *Behavioral Intention*, while *Habit* ($\beta = 0.352$, $p < 0.001$), *Facilitating Conditions* ($\beta = 0.176$, $p < 0.001$), and *AI Literacy* ($\beta = 0.224$, $p < 0.001$) shape *Use Behavior*. Both *Use Behavior* ($\beta = 0.519$, $p < 0.001$) and *AI Literacy* ($\beta = 0.358$, $p < 0.001$) positively enhanced *Academic Performance*, confirming that the critical and skillful use of Gen AI leads to genuine learning gains. Moreover, *Academic Integrity* ($\beta = 0.027$, $p = 0.015$) significantly moderated the relationship between *Use Behavior* and *Academic Performance*, indicating that ethical commitment amplifies the educational value of Gen AI.

Theoretically, this study extends UTAUT2 by embedding ethical and cognitive constructs, offering a robust framework for explaining Gen AI-enabled learning outcomes. This calls for higher education institutions to embed AI literacy modules, establish ethics governance frameworks, and promote integrity-based policies to ensure responsible and performance-oriented AI adoption. Ultimately, the findings emphasize that Gen's true educational value lies not merely in technological efficiency but in amplifying human intellect and moral responsibility through literate and ethical engagement.

Keywords: *Generative Artificial Intelligence (GenAI), UTAUT2, AI Literacy, Academic Performance, Academic Integrity, Higher Education*

1. INTRODUCTION

The rapid advancement of Generative Artificial Intelligence (GenAI) technologies, such as ChatGPT, Gemini, and Copilot, has revolutionized higher education globally, offering unprecedented opportunities for academic productivity and learning innovation (Chan &

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Colloton, 2023; Chan & Colloton, 2024). These tools demonstrate remarkable capabilities in generating human-like text, synthesizing research data, and creating programming code, fundamentally transforming traditional academic practices. However, this technological disruption presents a critical ethical paradox: while Gen AI enhances efficiency, its misuse threatens academic integrity through AI-assisted plagiarism, unauthorized content generation, and data manipulation (McCabe et al., 2001a, 2001b).

This dichotomy mirrors global trends but remains understudied in developing nations, where technological adoption often outpaces the development of ethical frameworks (Ivanov et al., 2024). Existing research predominantly focuses on Western contexts (Sales de Aguiar, 2024; Strzelecki, 2024) or single-platform studies (e.g., ChatGPT) (Lee et al., 2024), neglecting the broader GenAI ecosystem and Indonesia's unique socio-educational landscape.

As Southeast Asia's largest digital economy, Indonesia reflects global trends but has critical distinctions. First, traffic dominance: Indonesia ranks third globally in GenAI application usage (7.83% of traffic share), surpassing developed nations such as Germany (5.1%) and Japan (4.9%) (Similarweb, 2024). Second, academic reliance: 74% of Indonesian university students use Gen AI weekly for assignments, with 55% admitting to "heavy dependency" for essay drafting, while 83% of faculty express concerns about rising academic dishonesty (Author's preliminary survey, 2024). Third, regulatory void: fewer than 15% of Indonesian universities enforce AI ethics policies, and only 8% provide detection tools (Advance HE 2023).

This paradox of high technological adoption coupled with low ethical governance creates a fertile ground for academic misconduct. Preliminary data reveal alarming patterns: 68% of Indonesian students submit AI-generated content without attribution, while only 12% of universities have formal AI ethics guidelines (Author's preliminary survey, 2024). This regulatory vacuum exacerbates the risks in a system already strained by resource constraints and educational disparities.

Prior research has largely employed adoption-centric models, such as the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al., 2012). These models explain how constructs such as performance expectancy, effort expectancy, social influence, facilitating conditions, and habit shape behavioral intention and the use of new technologies (Dwivedi et al., 2023; Aljanabi et al., 2023). However, UTAUT2 has been critiqued for its ethical blindness, as it does not account for how ethical considerations influence outcomes beyond mere adoption (Kasneci et al., 2023). In the context of GenAI, where ethical misuse is prevalent, extending UTAUT2 with new variables is theoretically and practically warranted.

This study introduces AI Literacy and Academic Integrity as critical extensions. AI literacy refers to the ability to understand, critically evaluate, and responsibly apply AI tools to academic tasks (Ng et al., 2021; Kohnke et al., 2023). Students with higher AI literacy are more likely to use GenAI effectively, ensuring that outputs are verified, contextualized, and ethically applied, which should directly enhance both use behavior and academic performance (Kim et al., 2024). Meanwhile, academic integrity reflects students' ethical standards in academic conduct, including honesty, responsibility, and fairness (Kasneci et al., 2023; Ramdani, 2018). By moderating the relationship between use behavior and performance, academic integrity may strengthen the benefits of Gen AI by ensuring responsible usage.

Therefore, this study moves beyond adoption to focus on the academic outcomes of Gen AI use, integrating ethical and cognitive dimensions that are absent in prior models.

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Specifically, this study addresses the following research questions.

- RQ1. What factors influence students' intentions and actual use of generative AI in higher education?
- RQ2. How does students' literacy in artificial intelligence shape the effectiveness of its use and the outcomes of their learning?
- RQ3. To what extent do generative AI tools contribute to improving students' academic performance?
- RQ4. How do students' ethical standards and commitment to academic integrity influence the relationship between AI use and learning outcomes?

By incorporating AI literacy and academic integrity into the UTAUT2 framework, this study advances the theory and practice. Theoretically, it extends the UTAUT2 by integrating cognitive and ethical dimensions, offering a more holistic model of Gen AI use in higher education. Practically, the findings will inform policymakers and universities on how to balance innovation with responsibility, highlighting the importance of literacy-building interventions and integrity-promoting strategies to maximize the benefits of GenAI for student learning.

2. LITERATURE STUDY

2.1 UTAUT2 Framework through GenAI

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) explains technology adoption through constructs, Theoretical applicability from UTAUT2 in Gen AI contexts:

Table 1. Core UTAUT2 Constructs and GenAI Relevance

Construct	Definition	GenAI Manifestation
Performance Expectancy	Perceived benefits for task performance	"GenAI improves my grades"
Effort Expectancy	Ease of use	"Learning ChatGPT is easy"
Social Influence	Peer/community pressure	"My classmate recommends using Copilot"
Facilitating Conditions	Institutional support/resources	"Campus provides free AI tools"
Habit	Automatic usage patterns	"I use ChatGPT daily without thinking"

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Performance expectancy (PE) refers to the degree to which individuals believe that using a technology enhances their task performance (Venkatesh et al., 2012). In the context of generative AI (GenAI) adoption in higher education, PE captures educators' and students' perceptions of whether GenAI can support academic tasks, such as lesson planning, assignment generation, and assessment design. Prior studies have indicated that GenAI is perceived as particularly useful for improving productivity, writing quality, and comprehension (Kasneci et al., 2023; Pfeffer et al., 2023; Bouteraa et al., 2024; Budhathoki et al., 2024; Strzelecki & ElArabawy, 2024). Similarly, Menon and Shilpa (2023) and Gulati et al. (2024) found that performance benefits strongly shape behavioral intentions toward AI adoption. Thus, if educators and students perceive GenAI as a tool that meaningfully enhances academic effectiveness, their likelihood of adoption increases.

H1 : higher performance expectancy will lead to greater behavioral intention to use GenAI

Effort expectancy (EE) refers to the perceived ease of using a technology (Venkatesh et al., 2012). In educational settings, EE reflects the degree to which educators and students feel comfortable and find it simple to use GenAI tools. Several studies have confirmed that Gen AI applications such as ChatGPT are perceived as intuitive and user-friendly, which positively influences their adoption (Lee et al., 2024; Strzelecki, 2023b; Polyportis & Pahos, 2024; Küchemann et al., 2023; Bitzenbauer, 2023). Budhathoki et al. (2024) and Foroughi et al. (2023) further emphasize that minimizing the learning curve is essential for integration into teaching and learning. Hence, EE remains a critical determinant of whether academics incorporate Gen AI into their daily practices.

H2 : Effort expectancy have a positive effect on behavioral intention

Social influence (SI) denotes the extent to which individuals' decisions to adopt a technology are shaped by the opinions of peers, colleagues and institutional stakeholders (Venkatesh et al., 2003). In higher education, SI highlights how the perspectives of colleagues, administrators, and student peers shape the acceptance of Gen AI. Evidence shows that when educators receive positive feedback about Gen AI from their academic networks, their intention to use it significantly increases (Lee et al., 2024; Strzelecki, 2023a; Opara et al., 2023; Dawa et al., 2023; Romero Rodríguez et al., 2023). Strzelecki and ElArabawy (2024) and Bouteraa et al. (2024) demonstrate that peer recommendations are strong adoption drivers in academic settings. Therefore, SI plays a pivotal role in normalizing the use of Gen AI across universities.

H3: social influence will increase student's behavioral intention to use GenAI

Behavioral intention (BI) refers to an individual's readiness or willingness to use technology (Davis, 1989; Venkatesh et al., 2012). In education, BI predicts the actual adoption of GenAI for teaching and learning. Studies have consistently shown that educators and students with strong intentions to adopt educational technologies are more likely to engage in sustained usage (Bouteraa et al., 2024; Lee et al., 2024; Strzelecki, 2023a; Polyportis & Pahos, 2024). Research also indicates that BI is strongly shaped by PE, EE, and SI, aligning with previous UTAUT2 findings (Khong et al., 2022; Khong et al., 2023). Consequently, BI serves as a critical bridge between perception-driven factors and the actual use of Gen AI in higher education.

H4 : Behavioral have a positive effect on use behavior of GenAI

Facilitating conditions (FC) capture the degree to which individuals believe that organizational and technical infrastructure supports the use of a technology (Venkatesh et al., 2003). In the case of GenAI, FC includes access to AI platforms, institutional training, and reliable, technical

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assistance. Prior research has highlighted that sufficient infrastructure and institutional support are prerequisites for sustained adoption (Ateş & Garzón, 2023; Buraimoh et al., 2023; Budhathoki et al., 2024). Menon and Shilpa (2023) and Gulati et al. (2024) further emphasize that when universities provide official access and guidelines for GenAI usage, students and educators are more likely to incorporate it effectively into academic tasks. Thus, the FC is indispensable for fostering long-term integration.

H5 **:** *Facilitating Conditions positively influence Use Behavior of GenAI*

Habit (HB) is defined as the extent to which individuals automatically engage with technology owing to repeated use (Venkatesh et al., 2012). In higher education, HB manifests when educators and students use Gen AI as a routine part of their academic workflow without deliberate consideration. Prior studies have shown that educators with established habits of technology use are more inclined to adopt emerging innovations such as GenAI (Hu et al., 2020; Raman & Don, 2013). Recent findings further confirm that habitual reliance on AI tools predicts sustained engagement (Biloš & Budimir, 2024; Chávez Herting et al., 2023; Strzelecki, 2023). Therefore, HB is a strong predictor of GenAI use behavior in academic contexts.

H6 : habit will have a positive effect on use behavior of GenAI

2.2 AI Literacy

AI literacy (AL) is broadly conceived as a multi-dimensional competence set that enables individuals to understand, use, and evaluate AI systems responsibly (Asghar et al., 2025; Yang et al., 2025). In cognitive terms, it includes conceptual knowledge of AI algorithms and data, that is, knowing the basic functions of AI and how it works (Liu et al., 2025). Behaviorally, it entails practical skills, such as crafting effective prompts and meaningfully applying AI tools in different scenarios (Liu et al., 2025). Crucially, AI literacy also incorporates an ethical dimension: literate users recognize AI's potential biases, privacy issues, and societal impacts and learn to use AI wisely and ethically (Yang et al., 2025). Yang et al. (2025) define AI literacy as a set of competencies that allow individuals "to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool" in their daily lives. Similarly, foundational frameworks emphasize the ability to "know and understand AI," to "apply AI" in tasks, to "evaluate and create AI," and to practice AI ethics (Asghar et al., 2025; Liu et al., 2025). These overlapping definitions make it clear that AL spans the cognitive, behavioral, and ethical facets of generative AI use, ensuring that students are not only technically proficient but also critically reflective about AI's role.

AI literacy directly supports the effective and responsible use of generative AI tools. Students with higher AL are better able to exploit AI as a learning aid rather than as a crutch. For instance, literate users learn to generate better prompts and critically evaluate AI outputs, reducing their blind reliance on generated content (Liu et al., 2025). In practice, this means learning to use AI applications ethically in everyday life (Ng et al., 2021, as cited in Asghar et al., 2025). Educational experts advocate embedding AL in the curriculum; for example, curriculum designers should include dedicated courses or modules on AI (e.g., "AI for metacognitive planning") so that students acquire goal-setting and evaluative skills when using AI (Yang et al., 2025). Such training reinforces responsible AI use and problem solving. Iqbal et al. (2025) recommend that schools adopt technological-pedagogical frameworks (e.g., TPACK-based AI modules) and AI resource hubs to address students' skill gaps and ethical awareness. In summary, a literate student approaches GenAI tools with guidance and caution, applying them meaningfully, ethically, and effectively to learning tasks (Bećirović et al., 2025; Liu et al., 2025).

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H7 : AI literacy is expected to positively influence students' actual use behavior

H8 : AI literacy positively affects academic performance

2.3 Academic Performace

Academic performance (AP) represents the extent to which students achieve desirable learning outcomes in higher education, encompassing cognitive mastery, quality of academic output, and achievement indicators such as grades or GPA. Traditionally, AP has been conceptualized as a multidimensional construct that integrates objective measures (e.g., test scores, GPA) and subjective assessments (e.g., self-perceived learning gains) (Tarhini et al., 2017). In the context of Generative AI (GenAI), AP acquires new layers of complexity, as AI tools can both enhance and potentially undermine genuine learning outcomes, depending on how students engage with them.

Recent studies suggest that GenAI tools can contribute positively to AP by improving students' efficiency, cognitive engagement and the quality of their assignments. For example, Zou et al. (2023) reported that the responsible integration of Gen AI enhances academic output and time management, allowing students to focus on higher-order thinking. Similarly, Aljanabi et al. (2023) emphasized that students who use AI responsibly demonstrate improved comprehension and writing clarity. These findings align with the broader perspective that academic performance can be improved when AI is used as a learning support tool rather than as a replacement for students' cognitive effort (Kasneci et al., 2023; Dwivedi et al., 2023).

AP is structured into three main dimensions. First, academic output quality relates to the clarity, accuracy, and originality of student assignments or projects, where AI may provide scaffolding for better structure and coherence (Zhai 2022; Salinas-Navarro et al. 2023). Second, cognitive understanding refers to the ability to comprehend and critically engage with concepts, which Gen AI can foster through explanations and personalized tutoring, but risks eroding if students over-rely on unverified outputs (Kim et al., 2024; Barrett & Pack, 2023). Third, academic achievement encompasses formal indicators such as GPA, test results, and timely task completion, with early evidence showing positive correlations between ethical AI use and improved academic performance (McDonald et al., 2025).

H9 : Use behavior has a positive effect on academic performance

2.4 Academic Integrity

Academic integrity is defined as an ethical commitment to honesty, fairness, and responsibility in academic practices (Holden et al., 2021; Ramdani, 2018). In the context of generative AI (GenAI), integrity plays a crucial role in shaping not only adoption but also the outcomes of technology use. Bouteraa et al. (2024) found that integrity negatively influenced direct ChatGPT usage, as students with stronger ethical standards adopted AI more cautiously. Furthermore, integrity exerted complex moderating effects: it strengthened the relationship between effort expectancy and usage but weakened the influence of performance expectancy and technology self-efficacy. These findings suggest that integrity acts as a filter through which students critically evaluate AI tools' use. Supporting studies also indicate that learners with high integrity are more likely to engage in responsible and reflective use of Gen AI, reducing the risks of plagiarism or overreliance (Kasneci et al., 2023; Cotton et al., 2023). Conversely, low integrity levels are often associated with academic dishonesty and the misuse of AI-generated content (Dwivedi et al., 2023). Extending this reasoning, integrity is expected to ensure that Gen AI outputs are verified, attributed, and meaningfully applied to enhance learning.

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H10 : Academic integrity positively moderate the relationship between GenAI use behavior and academic performance

Table 2. Dimensions of Academic Integrity (Ramdani-Based Framework)

Dimension	Definition	Moderating Role
Honesty	Truthfulness in academic conduct	Rejects unverified AI submissions
Plagiarism Avoidance	Proper attribution of sources	Ensures AI content is explicitly cited
Ethical Resource Use	Appropriate technology application	Uses GenAI within institutional guidelines
Learning Responsibility	Ownership of knowledge acquisition	Limits AI dependency for core understanding
Fairness	Equitable participation in assessments	Avoids AI advantages in graded work

2.5. Integrating UTAUT2 with Academic Performance and Ethical Constructs

While UTAUT2 has been widely used to predict technology adoption behaviors in educational settings, it has rarely been extended to investigate how such adoption translates into learning outcomes, particularly in the context of emerging technologies like GenAI.

To address this gap, we propose a conceptual model that combines the following:

- UTAUT2 core constructs to explain students' behavioral intention and use behavior toward GenAI,
- Academic Performance (AP) as the ultimate academic outcome,
- and Academic Integrity (AI) and Academic Dishonesty (AD) as ethical variables influencing or moderating the impact of Gen AI use.

The resulting model includes nine hypotheses grouped into core behavioral and ethical-academic hypotheses.

3. METHODOLOGY

This study employs quantitative methods to comprehensively examine the factors influencing the use of GenAI and its effect on academic performance. This methodology integrates quantitative surveys of Indonesian higher education students.

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3.1 Research Framework

This study extends the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) by integrating constructs related to academic performance (AP), AI literacy (AL), and academic integrity (AI) within the context of Generative AI (GenAI use among university students (Fig. 1). The framework builds on the core UTAUT2 pathways (Performance Expectancy, Effort Expectancy, and Social Influence → Behavioral Intention → Use Behavior; Facilitating Conditions and Habit → Use Behavior) while incorporating new dimensions to capture the cognitive and ethical aspects of GenAI adoption.

Specifically, three additional constructs were introduced.

- Academic Performance (AP): The ultimate outcome variable, measured across three dimensions: Academic Output Quality (assignment quality, writing clarity, content accuracy), Cognitive Understanding (comprehension, critical thinking, reflection), and Academic Achievement (GPA, assignment completion, and test scores).
- AI Literacy (AL): Conceptualized as students' competence in understanding, critically evaluating, and responsibly applying GenAI in academic contexts. AL was modeled as a predictor of use behavior (UB) and a direct predictor of academic performance (AP).
- Academic Integrity (AI): Operationalized as a moderating variable that strengthens the positive relationship between use behavior (UB) and academic performance (AP). Students with higher academic integrity are expected to use GenAI more responsibly, thereby maximizing its learning benefits.

Through this framework, the study shifts its focus beyond adoption to examine how GenAI use translates into measurable academic outcomes and under what ethical conditions such outcomes are reinforced.

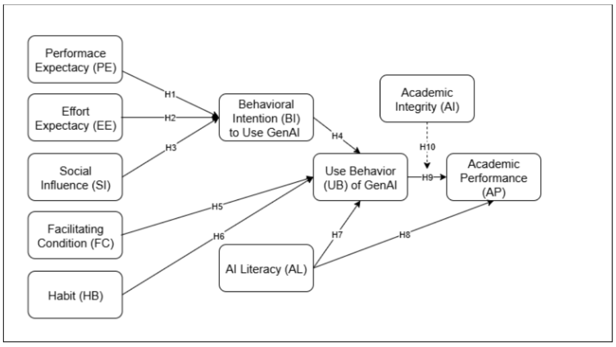

Figure 1. Research Model

3.2 Resarch Data

3.2.1 Data Collection

Sampling: Stratified random sampling of 1589 students from universities across Indonesia's ensuring representation of:

- Institution type (public/private)
- Discipline (STEM/humanities)
- GenAI experience level

Instrument:

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- 46-item questionnaire using 5-point Likert scales

3.2.2 Data Analysis

SEM-PLS Approach (SmartPLS 4.0):

1. Measurement model assessment
   - Convergent validity (AVE > 0.5)
   - Discriminant validity (Fornell–Larcker)
   - Reliability (α & CR > 0.7)
   - Multicollinearity Check (VIF < 5)
2. Structural model evaluation
   - Path coefficients (β)
   - t-values and p-values
   - Coefficient of Determination (R^2)
3. Multi-group analysis (MGA) for moderation testing

4. RESULTS AND DISCUSSION

4.1 Findings

4.1.1 Measurement Model

The evaluation of the measurement model demonstrated that all constructs in the modified UTAUT2 framework exhibited strong reliability and validity, ensuring the adequacy of the indicators and latent constructs used in this study.

Internal consistency reliability was established as all Composite Reliability (CR) values exceeded the 0.70 threshold, ranging from 0.862 to 0.963, while Cronbach's alpha values were also above 0.70, confirming acceptable reliability across constructs. Specifically, Academic Integrity (α = 0.795; CR = 0.862), AI Literacy (α = 0.914; CR = 0.932), Behavioral Intention (α = 0.889; CR = 0.923), and Academic Performance (α = 0.957; CR = 0.963) demonstrated particularly high internal consistency, indicating that their observed indicators consistently measured the intended latent variables.

Convergent validity was confirmed through Average Variance Extracted (AVE) values greater than the recommended 0.50 level, ranging from 0.564 to 0.779, signifying that each construct explained more than half of the variance in its indicators. All outer loadings were above 0.70, suggesting that the individual measurement items adequately reflected their associated constructs.

Discriminant validity was further supported by the Fornell–Larcker criterion, where the square roots of the AVE values for each construct exceeded their respective inter-construct correlations. For instance, the square root of the AVE for Academic Performance (0.863) was greater than its correlations with Use Behavior (0.833) and AI Literacy (0.797), confirming satisfactory discriminant validity among the constructs. Additionally, the Variance Inflation Factor (VIF) values ranged from 1.047 to 3.827, all below the conservative threshold of 5.0, indicating that multicollinearity was not an issue within the measurement model.

Overall, these results affirm that the measurement model satisfies the essential criteria

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for reliability and validity, allowing for a meaningful interpretation of the structural relationships in subsequent analyses. This aligns with prior SEM-PLS studies on GenAI acceptance in higher education (Strzelecki, 2024; Kasneci et al., 2023; Bouteraa et al., 2024), confirming the robustness of the extended UTAUT2 constructs in capturing the cognitive, behavioral, and ethical dimensions of Generative AI use in academic contexts.

Table 3. Validity and Reliability

Constructs	Indicators	Loadings	Cronbach's	CR	AVE
Performance Expectancy	PE1	0,897	0,892	0,925	0,755
	PE2	0,894			
	PE3	0,866			
	PE4	0,816			
Effort Expectancy	EE1	0,892	0,902	0,932	0,773
	EE2	0,891			
	EE3	0,890			
	EE4	0,845			
Social Influence	SI1	0,813	0,833	0,889	0,668
	SI2	0,871			
	SI3	0,730			
	SI4	0,848			
Facilitating Conditions	FC1	0,896	0,901	0,931	0,772
	FC2	0,888			

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Constructs	Indicators	Loadings	Cronbach's	CR	AVE
	FC3	0,902			
	FC4	0,827			
Habit	HB1	0,884	0,906	0,934	0,779
	HB2	0,856			
	HB3	0,895			
	HB4	0,896			
Behavioral Intention	BI1	0,884	0,889	0,923	0,751
	BI2	0,887			
	BI3	0,878			
	BI4	0,815			
Use Behavior	UB1	0,873	0,898	0,929	0,766
	UB2	0,838			
	UB3	0,886			
	UB4	0,903			
Academic Integrity	AI1	0,491	0,795	0,862	0,564
	AI2	0,771			
	AI3	0,846			
	AI4	0,860			

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Constructs	Indicators	Loadings	Cronbach's	CR	AVE
	AI5	0,728			
AI Literacy	AL1	0,823	0,914	0,932	0,697
	AL2	0,891			
	AL3	0,814			
	AL4	0,843			
	AL5	0,827			
	AL6	0,809			
Academic Performance	AP1	0,872	0,957	0,963	0,746
	AP2	0,838			
	AP3	0,862			
	AP4	0,874			
	AP5	0,817			
	AP6	0,874			
	AP7	0,871			

Table 4. Fornell-Larcker Criterion

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	Constructs	1	2	3	4	5	6	7	8	9	10
1	Academic Integrity	0,752									
2	AI Literacy	0,698	0,835								
3	Academic Performance	0,636	0,797	0,863							
4	Behavioral Intention	0,484	0,608	0,744	0,866						
5	Effort Expectancy	0,524	0,683	0,694	0,646	0,879					
6	Facilitating Conditions	0,603	0,769	0,781	0,743	0,695	0,879				
7	Habit	0,464	0,587	0,718	0,818	0,586	0,746	0,883			
8	Performance Expectancy	0,498	0,653	0,741	0,703	0,785	0,694	0,629	0,869		
9	Social Influence	0,543	0,628	0,695	0,761	0,684	0,705	0,683	0,701	0,817	
10	Use Behavior	0,538	0,703	0,833	0,780	0,659	0,778	0,799	0,702	0,693	0,875

Table 5. Variance Inflation Factor **(**VIF)

Relationship	VIF
Performance Expectancy → Behavioral Intention	3,005
Effort Expectancy → Behavioral Intention	2,872
Social influence → Behavioral Intention	2,163
Behavioral Intention → Use Behavior	3,451
Facilitating Conditions → Use Behavior	3,827
Habit → Use Behavior	3,466
AI Literacy → Use Behavior	2,465
AI Literacy → Academic Performance	2,800
Use Behavior → Academic Performance	2,056
Academic Integrity × Use Behavior → Academic Performance	1,047

4.1.2 Structural Model

The structural model was evaluated to assess the hypothesized relationships among the constructs and the explanatory power of the proposed framework. Path coefficients, *t*-values, and *p*-values were examined using a bootstrapping procedure with 5,000 resamples to ensure the statistical robustness.

All ten hypothesized paths demonstrated statistically significant relationships ($p < 0.05$), indicating strong support for the extended UTAUT2 model with ethical and cognitive extensions (AI Literacy and Academic Integrity). As presented in Table 6, **nine** of the hypothesized relationships were positive and significant, while **one**—the moderating effect of Academic Integrity—showed a weaker yet still significant moderating role.

Predictors of Behavioral Intention

Three constructs significantly influenced students' *Behavioral Intention* (BI) to use Generative AI. *Performance Expectancy* ($\beta = 0.294$, $t = 9.053$, $p < 0.001$) emerged as a strong determinant, suggesting that students are motivated to adopt GenAI primarily when they perceive it as enhancing their academic performance. This result corroborates the findings of Strzelecki (2024) and Menon and Shilpa (2023), who identified performance-related benefits as the dominant driver of AI adoption in higher education.

Effort Expectancy ($\beta = 0.068$, $t = 2.268$, $p = 0.024$) also had a positive and significant effect, implying that ease of use remains a relevant but secondary factor in determining intention, consistent with Polyportis and Pahos (2024). Likewise, *Social Influence* exhibited the strongest effect on intention ($\beta = 0.508$, $t = 18.022$, $p < 0.001$), highlighting the collective and normative nature of Gen AI adoption in university contexts, where peer recommendations and faculty attitudes heavily shape behavioral intentions (Bouteraa et al., 2024).

The model explained 63.7 % of the variance (Adjusted $R^2 = 0.637$) in *Behavioral Intention*, indicating substantial predictive power.

Determinants of Use Behavior

Use Behavior (UB) was significantly driven by *Behavioral Intention* ($\beta = 0.226$, $t = 5.837$, $p < 0.001$), *Facilitating Conditions* ($\beta = 0.176$, $t = 4.819$, $p < 0.001$), *habit* ($\beta = 0.352$, $t = 9.427$, $p < 0.001$), and *AI Literacy* ($\beta = 0.224$, $t = 8.816$, $p < 0.001$). These findings affirm that students' actual engagement with Gen AI depends not only on their intention but also on environmental readiness and habitual exposure.

The relatively high influence of *Habit* mirrors results by Strzelecki (2024) and Raman and Don (2013), confirming that habitual reliance on AI tools predicts sustained GenAI use. Meanwhile, the significant contribution of *AI Literacy* reflects that students with higher literacy levels are better able to operationalize GenAI effectively, ensuring responsible and performance-oriented application.

The model accounted for 75.1 % of the variance in Use Behavior (Adjusted $R^2 = 0.751$), representing a strong explanatory capacity for students' actual usage patterns.

Predictors of Academic Performance

Academic Performance (AP) was strongly influenced by both *Use Behavior* ($\beta = 0.519$, $t = 19.252$, $p < 0.001$) and *AI Literacy* ($\beta = 0.358$, $t = 9.808$, $p < 0.001$), confirming that students who actively and skillfully utilize GenAI tools can achieve better academic outcomes. This aligns with findings by Zou et al. (2023) and Aljanabi et al. (2023), who emphasized that GenAI supports task efficiency, comprehension, and output quality when applied ethically.

The moderating effect of *Academic Integrity* on the relationship between *Use Behavior* and *Academic Performance* was statistically significant, though modest ($\beta = 0.027$, $t = 2.438$, $p = 0.015$). This suggests that higher integrity enhances the positive impact of GenAI use on academic outcomes, ensuring that technological advantages translate into genuine learning achievements rather than academic misconduct. The moderation outcome supports the earlier theoretical expectations of Kasneci et al. (2023), showing that integrity acts as an ethical filter for AI-assisted learning.

The structural model explained 78.8 % of the variance in Academic Performance (Adjusted $R^2 = 0.788$), indicating excellent predictive validity and confirming that the inclusion of ethical and literacy variables substantially strengthened the explanatory power of the model beyond traditional UTAUT2 constructs.

Overall Model Evaluation

All *Variance Inflation Factor (VIF)* values ranged from **1.047 to 3.827**, confirming the absence of multicollinearity among the constructs. The model's high explanatory power across Behavioral Intention, Use Behavior, and Academic Performance underscores its robustness in capturing both the behavioral and ethical determinants of GenAI utilization in higher education.

In summary, the structural model validates the following:

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1. Cognitive-behavioral factors (Performance Expectancy, Social Influence, Habit) remain central to shaping Gen AI use.
2. *AI Literacy* functions as a dual driver, enhancing both use and performance outcomes.
3. *Academic Integrity* acts as an ethical amplifier, strengthening the positive link between technology use and authentic learning performance.

These insights reinforce that Gen's academic value is maximized when technological adoption is complemented by institutional support for AI literacy and ethical awareness, positioning the extended UTAUT2 framework as a comprehensive model for understanding AI-enabled academic performance in developing country contexts.

Table 6. Hypotheses testing

Hypothesis	Relationship	Path Coefficient	t-value	p-value	decision
H1	Performance Expectancy → Behavioral Intention	0,294	9,053	0,000	Supported
H2	Effort Expectancy → Behavioral Intention	0,068	2,268	0,024	Supported
H3	Social influence → Behavioral Intention	0,508	18,022	0,000	Supported
H4	Behavioral Intention → Use Behavior	0,226	5,837	0,000	Supported
H5	Facilitating Conditions → Use Behavior	0,176	4,819	0,000	Supported
H6	Habit → Use Behavior	0,352	9,427	0,000	Supported
H7	AI Literacy → Use Behavior	0,224	8,816	0,000	Supported
H8	AI Literacy → Academic Performance	0,358	9,808	0,000	Supported
H9	Use Behavior → Academic Performance	0,519	19,252	0,000	Supported
H10	Academic Integrity × Use Behavior → Academic Performance	0,027	2,438	0,015	Supported

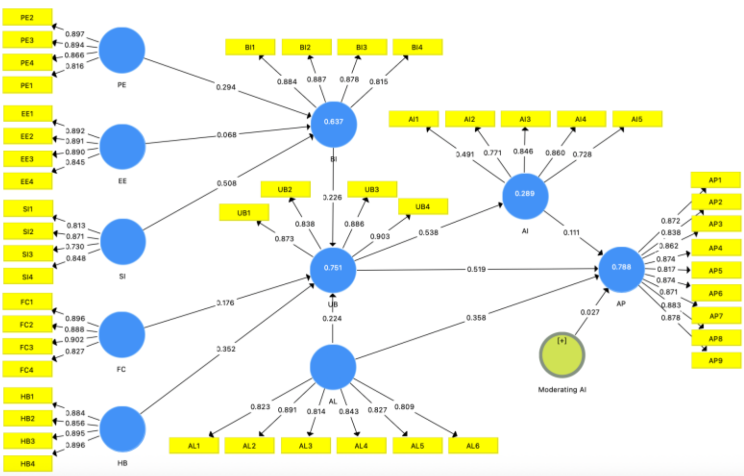

Figure 2. SEM-PLS Results

Table 7. R^2

Variables	Adjusted-R2	t-value	p-value	Decision
Academic Performance	0,788	57,721	0,000	Significant
Behavioral Intention	0,637	36,920	0,000	Significant
Use Behavior	0,751	50,549	0,000	Significant

4.2 Discussion

4.2.1 Key Findings

The findings of this study provide compelling empirical evidence that extends the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) by incorporating cognitive and ethical constructs—*AI Literacy* and *Academic Integrity*—to explain the influence of Generative AI (GenAI) use on *Academic Performance* in Indonesian higher education. The results validate the model's robustness and offer theoretical and practical insights into how Gen AI can enhance learning outcomes when adoption is supported by responsible and literate use.

Drivers of Behavioral Intention

The significant influence of *Performance Expectancy* ($\beta = 0.294$) and *Social Influence* ($\beta = 0.508$) on *Behavioral Intention* highlights that perceived usefulness and social endorsement are the primary motivations behind students' willingness to use Gen AI. This aligns with the findings of Strzelecki (2024) and Menon and Shilpa (2023), who found that students' motivation to adopt AI-based systems is strongly rooted in their expectations of enhanced academic productivity and peer validation.

In the Indonesian context, where collective and peer-driven behaviors are prevalent, social influence is of heightened importance. The strong effect of social influence suggests that recommendations from peers, lecturers, or online communities serve as behavioral reinforcers that normalize the use of GenAI in academic practices. Similar results were observed by Bouteraa et al. (2024), who emphasized that peer perception and social environments can accelerate technology diffusion in university ecosystems.

Although *Effort Expectancy* ($\beta = 0.068$) was significant, its smaller effect size indicates that ease of use, although relevant, is less critical for GenAI adoption—likely because these tools (e.g., ChatGPT, Gemini, Copilot) are already user-friendly. This echoes Polyportis and Pahos (2024), who observed that ease of use becomes less influential when students are already digitally competent. Thus, behavioral intention toward GenAI is shaped more by perceived utility and social validation than by usability concerns.

Factors Influencing Actual Use Behavior

The strong predictive power for *Use Behavior* (Adjusted $R^2 = 0.751$) underscores that both psychological readiness and contextual support shape how students operationalize GenAI. Consistent with Dwivedi et al. (2023), *Behavioral Intention* ($\beta = 0.226$) emerged as a key precursor of actual use, confirming that intention effectively translates into behavior within digitally mature student populations.

Facilitating Conditions ($\beta = 0.176$) and *habit* ($\beta = 0.352$) were also significant, reaffirming that continuous exposure and institutional support sustain Gen AI use. The role of *habit* —the strongest behavioral driver—aligns with Strzelecki (2024) and Raman and Don (2013), who demonstrated that habitual engagement with AI tools predicts persistence in technology-assisted learning. This suggests that Gen AI usage among students may already be transitioning from exploratory adoption to routine dependency.

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Importantly, *AI Literacy* ($\beta = 0.224$) emerged as a new and significant determinant of *Use Behavior*, substantiating theoretical propositions by Ng et al. (2021) and Yang et al. (2025) that literate users engage with AI tools more critically and responsibly. Literate students are not only more confident in prompt engineering and interpretation but also aware of GenAI's limitations and ethical boundaries. Thus, AI literacy bridges cognitive competence and behavioral sustainability, ensuring that frequent use does not devolve into dependence or misconduct.

Effects on Academic Performance

The results demonstrate that *Use Behavior* ($\beta = 0.519$) and *AI Literacy* ($\beta = 0.358$) are both powerful predictors of *Academic Performance* (Adjusted $R^2 = 0.788$), confirming that the responsible and skillful use of GenAI contributes substantially to learning outcomes. This finding corroborates Zou et al. (2023), who reported that AI-assisted study practices enhance cognitive understanding and academic productivity, and Aljanabi et al. (2023), who linked AI integration to improvements in writing quality and conceptual mastery.

Notably, *AI Literacy* plays a dual role: it enables the use of Gen AI and directly enhances academic performance. This indicates that the quality of learning outcomes is not solely determined by the frequency of use but also by *how* students engage with AI outputs. Students who possess critical literacy skills can verify, contextualize, and ethically apply GenAI-generated content, producing higher-quality academic outputs and a deeper cognitive understanding.

The moderating effect of *Academic Integrity* ($\beta = 0.027$, $p = 0.015$) confirms that ethical standards strengthen the positive relationship between Gen AI use and performance. This result resonates with Kasneci et al. (2023) and Cotton et al. (2023), who emphasized that integrity serves as a moral compass to guide responsible AI use in learning environments. High-integrity students are more likely to use Gen AI as a cognitive aid rather than as a shortcut, reinforcing genuine academic engagement. Conversely, the modest effect size may reflect Indonesia's limited institutionalization of AI ethics frameworks—only 15% of universities have formal AI use policies (Advance HE, 2023)—thus constraining the systemic impact of integrity moderation.

4.2.2 Theoretical Implications

This study advances the theory in three critical ways. First, it empirically extends **UTAUT2** by integrating *AI Literacy* as a cognitive dimension that captures users' evaluative competence and ethical awareness. The dual influence of AI Literacy on both Use Behavior and Academic Performance underscores its theoretical value in linking technological adoption with learning outcomes, an aspect neglected in traditional UTAUT2 applications.

Second, this study introduces *Academic Integrity* as a moral moderating construct that transforms UTAUT2 from a purely behavioral model into an ethically grounded framework. This integration addresses the "ethical blindness" of UTAUT2 highlighted by **Kasneci et al. (2023)** and enriches the model's explanatory scope by linking ethical behavior to academic outcomes.

Third, by demonstrating high explanatory power ($R^2\_AP = 0.788$), the model offers a new theoretical lens—the *Ethically Extended UTAUT2*—for studying AI adoption in learning environments, particularly in developing countries where ethical and regulatory infrastructures are still emerging.

4.2.3 Practical Recommendations

At the policy level, this study underscores the urgent need for national alignment between innovation and ethics in Indonesia's higher-education ecosystem. As universities increasingly integrate GenAI into teaching and assessment, policy frameworks must evolve to safeguard academic integrity without stifling innovation.

The key policy recommendations are as follows:

- National AI Literacy Strategy: The Ministry of Education and Directorate General of Higher Education should mandate AI literacy competencies as part of the national curriculum standards, ensuring that students and lecturers acquire both technical fluency and ethical discernment.
- AI Ethics Governance Frameworks: Universities must institutionalize integrity guidelines, transparent authorship rules, and monitoring systems for AI-assisted academic outputs.
- Cross-sector Collaboration: Partnerships between academia, policymakers, and the AI industry are essential to create standardized ethical guidelines and promote responsible AI integration that aligns with Indonesia's *Merdeka Belajar–Kampus Merdeka* vision.
- Periodic Evaluation and Accreditation Linkage: Ethical AI use indicators should be embedded in institutional accreditation criteria and performance evaluations to encourage systemic compliance and culture building.

These policies would ensure that the rapid adoption of AI tools in higher education does not erode academic honesty but instead strengthens digital and moral resilience among learners.

For university administrators and educators, this study highlights the necessity of designing AI-empowered learning ecosystems that integrate ethical awareness, literacy development, and supportive infrastructure. In practice, this means the following:

- Embedding AI literacy in learning outcomes and student orientation programs.
- Training lecturers to assess AI-assisted assignments fairly and transparently.
- Developing "AI Literacy Labs" where students can experiment responsibly under guided supervision.
- Promoting peer-led ethical initiatives to reinforce integrity as a shared academic value.

In this regard, GenAI should be reframed not merely as a productivity tool but as a pedagogical partner that enhances inquiry, creativity and ethical reasoning.

4.2.3 Limitations and Future Research

While this study provides valuable insights, several limitations provide opportunities for further inquiry.

1. Cross-sectional Design: The current study captures relationships at a single point in time. Future research should adopt longitudinal or experimental designs to observe causal changes in students' literacy, integrity and performance over time.
2. Self-reported Data Bias: As study relied on self-assessment, future studies could triangulate data using objective performance measures or learning analytics.
3. Cultural and Institutional Context: Given that this study focuses on Indonesian universities, replication in other emerging economies (e.g., Malaysia, India, and the Philippines) would

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strengthen the generalizability of the ethically extended UTAUT2 framework.

4. Inclusion of Additional Ethical Constructs: Future research may explore related constructs, such as *academic dishonesty*, *trust in AI*, or *AI transparency*, to provide deeper insights into ethical decision-making in AI-assisted learning.
5. Qualitative Extensions: Mixed-method approaches involving interviews or focus groups could reveal nuanced motivations, ethical dilemmas, and institutional narratives beyond quantitative correlations.

5. CONCLUSION

This study advances the understanding of the utilization of Generative Artificial Intelligence (GenAI) in higher education by moving beyond adoption-centered research and linking technology use directly to academic outcomes. Through a modified Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), extended with *AI Literacy* and *Academic Integrity* as ethical-cognitive variables, the model successfully explained 63.7% of the variance in *Behavioral Intention*, 75.1% in *Use Behavior*, and 78.8% in *Academic Performance*.

The empirical findings underscore that students' engagement with Gen AI tools is not merely a product of technological convenience but a reflection of their cognitive readiness and ethical awareness. Specifically, *Performance Expectancy* and *Social Influence* emerged as the strongest drivers of *Behavioral Intention*, affirming that both perceived usefulness and peer endorsement shape students' willingness to use AI in academic contexts. *Habit*, *Facilitating Conditions*, and *AI Literacy* significantly influenced *Use Behavior*, emphasizing that repeated exposure, institutional support, and cognitive competence jointly sustain responsible AI usage.

Moreover, *AI Literacy* and *Use Behavior* exerted strong positive effects on *Academic Performance*, validating that students who use GenAI strategically and critically achieve superior learning outcomes. Importantly, *Academic Integrity* acted as an ethical moderator, amplifying the positive relationship between GenAI use and academic results, indicating that integrity transforms technological benefits into genuine academic achievement rather than superficial performance gains.

Theoretically, this study contributes an *ethically extended UTAUT2 model* that integrates behavioral, cognitive, and moral dimensions to explain GenAI use in education. The inclusion of AI Literacy bridges the gap between adoption and academic outcomes, while Academic Integrity introduces an ethical lens long missing from technology-acceptance research. This model can serve as a foundation for future studies exploring responsible AI integration in diverse educational settings.

The findings call for a balanced strategy that combines innovation and ethical governance. Universities and policymakers should embed AI literacy training into curricula, institutionalize AI ethics frameworks, and promote academic integrity through clear guidelines and monitoring. Such measures will ensure that GenAI is not a shortcut for academic dishonesty but a catalyst for creativity, reflection, and learning excellence.

Ultimately, this study concludes that the true value of Generative AI in higher education lies not merely in its capacity to accelerate work but in its potential to amplify human intellect and moral responsibility. The responsible adoption of AI—grounded in literacy, integrity, and institutional support—can transform educational systems toward a more ethical, equitable, and intelligent future of learning.

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