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Research Article

Keywords: Generative artificial intelligence, technology adoption, academic integrity, policy internalization, higher education

Posted Date: June 8th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9481849/v1

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Additional Declarations: No competing interests reported.

Ethical Governance of Generative AI in Higher Education in the Absence of Binding Law

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Abstract: The rapid diffusion of generative artificial intelligence in higher education has outpaced the development of empirical and regulatory understanding of how such technologies are adopted and ethically governed. While existing research emphasizes early-stage acceptance or technical impacts, limited attention has been given to post-adoption contexts where Generative AI use has become routine and institutionally pervasive. This study addresses this gap by examining the distinct mechanisms underlying Generative AI adoption and ethical engagement among students and lecturers in Indonesian higher education. Using survey data from 311 respondents and partial least squares structural equation modeling, the findings show that behavioral intention is driven by habit, hedonic motivation, and social influence, while traditional acceptance factors are no longer salient. This indicates normalized academic use. Although behavioral intention remains a significant predictor of actual use, ethical behavior follows a different logic. Ethical generative AI behavior does not emerge from use itself but depends decisively on institutional governance and normative clarity.

Key words: Generative artificial intelligence; technology adoption; academic integrity; policy internalization; higher education.

1 Introduction

1.1 Research Background

The emergence of Generative Artificial Intelligence (generative AI) has marked one of the fastest technological diffusion processes in recent history, driven primarily by the rapid rise of generative large language models (LLMs). This diffusion has been spearheaded by ChatGPT, a conversational artificial intelligence system developed by OpenAI based on the Generative Pre-trained Transformer (GPT) architecture publicly released in late 2022, which gained over 100 million active users within only two months of its launch. This rapid expansion has been followed by other prominent models such as Bing by Microsoft, PaLM by Google, and LLaMA by Meta [1]. Trained on a diverse corpus of texts, including books, academic publications, and online sources, these generative LLMs demonstrate the ability to interpret user inputs, generate contextually relevant responses, and sustain coherent interactions across a broad spectrum of topics [2]. Both its transformative potential and adoption have been widely discussed across various sectors [3], including education.

Generative AI can support both lecturers and students by assisting teaching tasks such as lesson preparation and feedback, while also enabling learners to search for information, develop ideas, refine their work, and receive personalized academic support [4]. In higher education,

generative AI diffusion has been especially pronounced. Existing studies and surveys consistently report high levels of student engagement with generative AI for academic purposes, often exceeding 70% in university samples across multiple regions [5-7]. These patterns indicate that generative AI adoption in higher education is no longer driven by institutional implementation strategies, but by accessibility, platform availability, and strong alignment with existing academic practices. At the same time, this widespread adoption has raised ethical concerns, as well as reshaping the competency requirements for both students and lecturers [8]. A central issue relates to academic integrity, particularly ambiguity surrounding authorship, originality, and acceptable levels of AI assistance. This uncertainty combined with the lack of clear policies and institutional practices, has complicated governance in educational context, contributing to ethical violations [9]. This condition reflects a broader pattern observed in disruptive innovations, where rapid technological adoption outpaces institutional and regulatory readiness [10].

This governance challenge is further evidenced by the fact that only a limited number of countries have established legally enforceable laws specifically regulating the use of generative AI in education [11]. Most jurisdictions continue to rely on non-binding guidelines or general AI frameworks that lack sector-specific legal force. Consequently, enforcement mechanisms addressing the distinctive risks and practices of generative AI use in higher education remain limited and indirect. Within this regulatory landscape, this study focuses on Indonesia, where generative AI adoption in higher education has accelerated in the absence of clear and enforceable legal provisions. While the empirical focus is national, the Indonesian case reflects a broader condition shared by most countries, in which governance of generative AI in education remains fragmented and largely dependent on institutional discretion rather than statutory law. Such a condition is commonly described as legal vacuum, referring to the absence or inadequacy of binding legal frameworks to govern certain activities or situation resulting in legal uncertainty and limited enforceability [12].

1.2 Research Aim

This study aims to examine the adoption of generative AI in higher education within the context of a legal vacuum, focusing on how the absence of clear and enforceable legal frameworks shapes governance, ethical practices, and institutional responses. Drawing on empirical evidence from Indonesia, the study seeks to analyze how students and lecturers engage with generative AI amid regulatory uncertainty, while also identifying the legal and ethical implications arising from this condition. Beyond its contextual setting, the study is intended to provide an empirical basis for researchers, policymakers, and educational institutions to better understand and address the governance and ethical challenges associated with generative AI in higher education under conditions of regulatory uncertainty.

2 Methodology

This study adopts a quantitative research approach to explore the factors influencing the adoption of generative AI in higher education, with a focus on the Greater Jakarta area, Indonesia's metropolitan region. A survey-based

methodology is employed to capture large-scale data from a wide cross-section of respondents, providing a comprehensive view of both students and lecturers' attitudes, perceptions, and usage patterns concerning generative AI. To analyze the complex interrelationships among the constructs, the study utilizes Structural Equation Modeling (SEM). SEM is appropriate for this research because it allows the simultaneous evaluation of multiple latent variables and supports the assessment of both direct and indirect relationships within a single analytical framework [13].

2.1 Conceptual Framework and Hypotheses Development

The study builds upon the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), a widely recognized framework in technology adoption research that explains user behavior through constructs such as performance expectancy, effort expectancy, social influence, hedonic motivation, habit, and facilitating conditions [14]. While UTAUT2 captures the technological determinants of user behavior, this study extends the model by incorporating additional constructs related to institutional policy clarity and academic integrity culture. This extension enables a deeper examination of responsible generative AI adoption in academic environments, particularly under conditions of regulatory uncertainty.

The conceptual framework as can be seen in Fig. 1 integrates both technology acceptance theory and ethical governance considerations to investigate generative AI adoption in higher education. Building on the UTAUT2 model, the framework retains core determinants of technology use while expanding its scope to include constructs that reflect the ethical and institutional context in which generative AI is used.

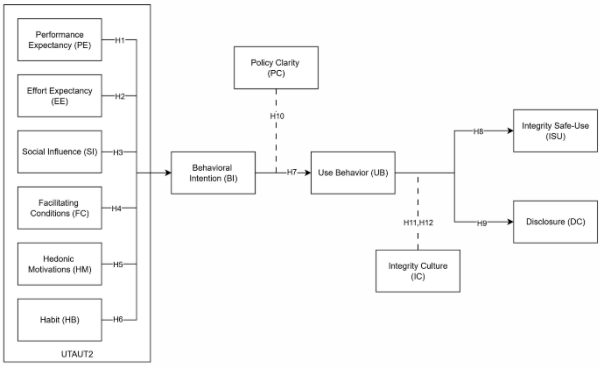

Fig. 1 Conceptual framework

2.2.1 Defining Constructs

The framework integrates six primary constructs from the UTAUT2 model, which serve as the basis for understanding behavioral intention (BI) and actual use behavior (UB) in relation to generative AI adoption.

1. *Performance Expectancy* (PE): The degree to which users believe that using generative AI enhances academic performances.
2. *Effort Expectancy* (EE): The perceived ease associated with using generative AI, whereby technologies that are easier to use are more likely to be adopted.
3. *Social Influence* (SI): The extent to which peers, colleagues, and the broader academic community influence individuals' decisions to use generative AI.
4. *Facilitating Conditions* (FC): The availability of organizational and technical resources that enable and facilitate the use of generative AI.
5. *Hedonic Motivations* (HM): The degree of enjoyment and satisfaction derived from using generative AI.
6. *Habit* (HB): The extent to which the

use of generative AI becomes embedded in routine academic activities.

7. *Behavioral Intention* (BI): User intention to adopt or use generative AI.
8. *Use Behavior* (UB): Actual usage of generative AI.

While these constructs provide insight into the adoption of generative AI, additional constructs are incorporated to address the unique ethical dimensions associated with this technology in academic settings.

9. *Policy Clarity* (PC): The degree to which institutional guidelines governing the use of generative AI are clear, explicit, and accessible. Clear policy guidance reduces interpretive ambiguity and provides concrete reference points for acceptable practices when dealing with emerging digital technologies [15], particularly in contexts characterized by rapid innovation and regulatory lag [16].
10. *Integrity Culture* (IC): The shared ethical norms and values within an academic institution that shape expectations of honest, responsible, and accountable conduct. Such cultural norms influence individual behavior through social reinforcement and collective expectations, often exerting a stronger effect than formal rules alone [17].
11. *Integrity Safe-Use* (ISU): The extent to which individuals apply generative AI in ways that are consistent with academic ethical standards. Responsible use requires ongoing judgement and accountability when interacting with automated and generative outputs [18].
12. *Disclosure* (DC): The extent to which users openly acknowledge their use of generative AI in academic work. Transparency supports fair evaluation and academic accountability [19].

2.2.2 Hypotheses Formation

The relationships among these constructs form the foundation for the following hypotheses, formulated based on the theoretical foundations of technology adoption and ethical behavior.

Hypotheses Related to Technology Adoption

H1: PE positively influences BI to use generative AI

H2: EE positively influences BI to use generative AI

H3: SI positively influences BI to use generative AI

H4: FC positively influences BI to use generative AI

H5: HM positively influences BI to use generative AI

H6: HB positively influences BI to use generative AI

H7: BI positively influences actual UB

Hypotheses Related to Ethical Constructs

H8: UB positively influences ISU. Frequent interaction with generative AI is expected to lead to more ethical usage practices as users become more aware of its potential implications

H9: UB positively influences DC. As users become more familiar with generative AI through frequent usage, it is expected that they will become more comfortable with openly acknowledging its use in academic work

Effects of Policy and Integrity Culture

H10: PC positively influences ISU. Clear institutional guidelines and policies help

users understand the ethical boundaries for using generative AI, ensuring that their usage aligns with academic integrity standards

H11: PC positively influences DC. Clear and well-defined policies reduce uncertainty, making users more comfortable being transparent about their use of the technology in their academic work.

H12: IC positively influences ISU. A strong integrity culture within academic institutions promotes ethical behavior among students and faculty.

H13: IC positively influences DC. An academic institution that emphasizes a strong integrity culture encourages its members to adhere to ethical standards and promotes an environment of openness.

2.2 Scope of the Study

This study primarily focuses on students and lecturers from universities within the Greater Jakarta area, Indonesia's metropolitan region. It is assumed that this area represents the highest level of generative AI adoption, considering its role as the central hub of educational and technological advancements in the country. However, to broaden the scope and provide a more comprehensive analysis, respondents from outside the Greater Jakarta area are also included in the study. This additional data allows for a comparative analysis, giving valuable insights into how generative AI adoption varies across different regions of Indonesia's higher education system.

Respondents of this study are those who have used or have been exposed to generative AI tools in their academic activities. This includes those who have been engaged with generative AI for various academic tasks. Given the scope of the research and the diversity of participants, a stratified random sampling technique is utilized to ensure that the sample reflects the different academic roles and university locations. The sample distribution is allocated across several regions within the Greater Jakarta area, as well as additional respondents from outside the area. The sample distribution across different regions is proportional to the population size in each area.

2.3 Instrumentation and Data Collection

Data for this study were collected through a structured questionnaire designed to capture both technological and ethical aspects of generative AI adoption in higher education. The instrument was developed based on the UTAUT2 model and the additional ethical constructs introduced in the conceptual framework, as outlined in the previous section. It aimed to measure respondents' attitudes, behaviors, and perceptions regarding generative AI adoption.

The questionnaire consists of four main sections. The first section focuses on demographic information, including questions about the respondent's gender, age group, academic status (whether they are a student or lecturer), and the level of education (for students) or teaching experience (for lecturers). This section also inquires about the respondent's primary field of study and the type of institution they are affiliated with. The second section assesses general questions regarding generative AI usage. It includes questions on respondents' frequency of use and the primary purposes for using generative AI in academic settings. The third section measures the technology adoption constructs from the UTAUT2 model, including performance expectancy, effort

expectancy, social influence, facilitating conditions, hedonic motivation, and habit. The final section focuses on ethical constructs and policy. It examines respondents' perceptions of policy clarity and ethical use of generative AI in academic work.

To ensure comprehensive data collection, the questionnaire included a Likert scale, multiple-choice questions, and some open-ended questions, allowing for both quantitative and qualitative analysis. The Likert scale was employed to measure respondents' attitudes and perceptions towards the constructs on a five-point scale, ranging from strongly disagree to strongly agree [20-21].

The data collection process was conducted online. Prior to full deployment, the survey instrument underwent a pilot test with a small group of students and lecturers to assess clarity, reliability, and validity. This pilot testing ensured that the questions were well understood and appropriately aligned with the research objectives.

Ethical considerations were strictly adhered to throughout the data collection process. Participants were fully informed about the purpose of the study, their voluntary participation, and their right to withdraw at any time without consequence. All responses were anonymized, and participants were assured that their data would be used strictly for academic research purposes. Informed consent was obtained from all participants before they started the survey.

2.4 Analytical Strategy

Data analysis followed the standard workflow for Partial Least Squares Structural Equation Modeling (PLS-SEM), aligned with the constructs, indicators, and hypothesis structure defined in this study.

2.4.1 Measurement Model Evaluation

The measurement model was first assessed to confirm the validity and reliability of the reflective constructs. This included assessing convergent validity through factor loadings and Average Variance Extracted (AVE), examining internal consistency reliability using Cronbach's Alpha and composite reliability, and reviewing indicator performance for possible refinement of the model [13].

2.4.2 Structural Model Evaluation

After establishing measurement validity, the structural model was examined to evaluate the hypothesized relationships. This stage involved estimating path coefficients for all directional links, assessing co-linearity through VIF values, determining model explanatory power using the coefficient of determination R^2, and assessing each predictor's relative contribution through effect size (f^2) [13].

2.4.3 Bootstrapping for Hypotheses Testing

Hypothesis testing was conducted using a non-parametric bootstrapping procedure, in line with the analytical approach presented in this research. The resampling process generated including t-statistics, p-values, and confidence intervals needed to assess the statistical significance of each hypothesized relationship [13].

3 Results

3.1 Descriptive Profile of Respondents

A total of 311 respondents participated in this study, comprising individuals from higher education institutions located both within and outside the Greater Jakarta region.

Table 1 Demographic information (n = 311)

Category	Group	(%)
Gender		
	Male	54.8
	Female	45.2
Age		
	16-27 years old (Gen Z)	68.0
	28-48 years old (Millennial)	22.4
	49-60 years old (Gen X)	8.9
	> 60 years old (Baby Boomer)	0.6
Academic Role		
	Active student	82.6
	Lecturer	17.4
Education Level		
	Diploma	3.2
	Bachelor	58.5
	Master	23.2
	Doctoral	8.4
Lecturer Experience		
	< 5 years	5.5
	5-10 years	6.1
	11-20 years	4.2
	> 20 years	3.9
Field of Study		
	STEM	33.8
	Non-STEM	66.2
Institutional Type		
	Public	78.8
	Private	21.2
Frequency of Generative AI Use		
	Almost every day	40.3
	A few times per week	39.6
	Once a week	3.0
	Less than once per week	4.6
	Used it but not routinely	12.5

Table 1 above summarizes the demographic and institutional characteristics of the respondents. The sample shows a near-balanced gender distribution and is dominated by younger cohorts, particularly Generation Z, while also including respondents from older generations, supporting variation in digital familiarity and ethical perspectives. Most respondents are students, complemented by lecturers whose participation provides instructional and professional viewpoints. Educational backgrounds range from diploma to doctoral levels, with bachelor's degree holders forming the largest group. The sample span both STEM and non-STEM disciplines and includes participants from public and private universities, enabling comparisons across disciplinary and institutional contexts. Patterns of use frequency indicate that generative AI is routinely integrated into academic activities, providing a robust empirical basis for analyzing adoption, governance, and ethical engagement in Indonesian higher education.

3.2 SEM Evaluation Result

3.2.1 Measurement Model Evaluation Result

The evaluation of the measurement model focuses on assessing whether the observed indicators adequately represent the latent constructs examined in this study. This process involves the assessment of convergent validity and internal consistency reliability, both of which are essential components of reflective measurement models in PLS-SEM. According to foundational guidelines in measurement theory [22-23], convergent validity reflects the extent to which indicators of a construct share a high proportion of variance, while reliability refers to the consistency of measurement across indicators.

Convergent validity was assessed using factor loadings, with a commonly accepted threshold of 0.70 indicating adequate reliability and that at least 50% of the variance in the latent construct is explained [11]. The results show that almost all indicators achieved loadings above this threshold, confirming strong convergent validity across the measurement model. One exception was indicator FC2, which exhibited a substantially lower loading. This deviation is theoretically explainable, as FC2 captures institutional-level support while FC1 reflects individual access to resources. This indicates that the FC construct encompasses heterogeneous dimensions rather than a single reflective factor. Importantly the presence of a single low-loading indicator does not compromise overall measurement quality, as the remaining indicators demonstrate satisfactory convergence.

Convergent validity was further supported by Average Variance Extracted (AVE) with all constructs achieving values above the recommended threshold of 0.50[24]. Internal consistency reliability, assessed using Cronbach's Alpha, showed that nearly all constructs exceeded acceptable levels ($\alpha \geq 0.60$) and most demonstrated strong reliability ($\alpha \geq 0.70$) [24]. An exception was observed for FC construct, which exhibited a lower Alpha value, consistent with the conceptual heterogeneity identified in the factor loading analysis.

Overall, the measurement model demonstrated sufficient robustness to support subsequent structural analysis. The high consistency of most constructs indicates stable respondent perceptions, while the observed irregularities in FC construct highlight meaningful variation in institutional support and digital readiness that informs the interpretation of structural relationships examined in later sections.

3.2.2 Structural Model Evaluation Result

The structural model was evaluated using the coefficient of determination (R^2) where values of 0.67, 0.33, and 0.19 indicate substantial, moderate, and weak explanatory power, respectively [24-25]. The results show that Behavioral Intention (BI) achieved substantial explanatory power ($R^2 = 0.705$), while Integrity Safe-Use (ISU) demonstrated moderate explanatory power ($R^2 = 0.557$). In contrast, actual Use Behavior (UB) ($R^2 = 0.233$) and Disclosure ($R^2 = 0.218$) exhibited weak explanatory power, indicating that intention and usage frequency alone are insufficient to explain actual engagement and disclosure practices. The moderate R^2 for ISU highlights the role of institutional factors, particularly integrity culture and policy clarity, in shaping ethical behavior, whereas weak R^2 for DC suggests that disclosure decisions are more context-dependent and influenced by situational judgement.

Effect size analysis (f^2) further clarifies predictor importance, with values of 0.02, 0.15, and 0.35 indicating small, medium, and large factors [24, 26]. The results indicate that habit (HB) exerts a large effect on behavioral intention, while hedonic motivation (HM) shows a moderate effect, highlighting the central role of routine use and intrinsic enjoyment in shaping generative AI adoption. In contrast, performance expectancy (PE), effort expectancy (EE), and facilitating conditions (FC) display negligible effects. This pattern suggests that, in the context of generative AI, traditional perceptions of usefulness and ease of use are less decisive, as these tools have become widely accessible and

intuitive.

The analysis of path coefficients provides further insight into the relative strength and direction of the relationships among constructs. BI strongly predicts UB (β = 0.466), with HB (β = 0.451) and HM (β = 0.317) emerging as the strongest antecedents of intention followed by SI (β = 0.151) and EE (β = 0.104) PE (β = -0.036) and FC (β = -0.061) show negative effects, indicating that perceived usefulness and resource availability play a limited role in shaping intention in generative AI context.

For ethical pathways, IC strongly influences ISU (β = 0.664) and moderately affects DC (β = 0.368), highlighting the central role of shared ethical norms in guiding responsible and transparent generative AI practices. Policy Clarity (PC) shows smaller but positive effects on both DC (β = 0.166) and ISU (β = 0.127), suggesting that formal guidelines contribute to ethical engagement, although to a lesser extent than cultural factors. In contrast, UB has minimal effects on both DC (β = 0.064) and ISU (β = 0.040), reinforcing the conclusion that ethical and transparent generative AI use does not naturally arise from increased usage frequency but depends primarily on institutional and normative cues.

Overall, the structural model reveals two distinct dynamics in generative AI engagement. Adoption is driven primarily by personal motivation and habitual use, indicating that generative AI is embedded in routine academic practice. However, ethical use is shaped mainly by institutional conditions rather than individual interaction. This divergence suggests that responsible generative AI behavior depends on institutional guidance and normative clarity. The model therefore positions adoption and ethical engagement as related yet fundamentally separate processes, each governed by its own set of influences within the extended UTAUT2 framework.

3.2.3 Hypotheses Testing Result

Hypothesis testing was conducted using a two-tailed bootstrapping procedure, which assesses whether each structural path differs significantly from zero without assuming a predetermined direction of effect [24, 27]. In the context of PLS-SEM, a hypothesis is considered supported when the empirical t-statistic meets or exceeds the critical value of 1.96 at the 5% significance level, or when the associated p-value is below 0.05[24]. The bootstrapping results presented in Table 2 and Fig. 2 provide estimates of the original path coefficients along with their standard deviations, allowing for evaluation of both effect magnitude and sampling variability.

Table 2 Hypotheses testing result

Path	Beta (O)	STDEV	T-stat	p-value	Significant? (p < 0.05)
BI→UB	0.485	0.052	9.353	0.000	Yes
EE→BI	0.030	0.061	0.487	0.313	No
FC→BI	-0.022	0.052	0.416	0.339	No
HB→BI	0.422	0.066	6.391	0.000	Yes
HM→BI	0.325	0.072	4.501	0.000	Yes
IC→DC	0.366	0.059	6.240	0.000	Yes
IC→ISU	0.707	0.041	17.141	0.000	Yes
PC→DC	0.152	0.079	1.928	0.027	Yes
PC→ISU	0.138	0.039	3.534	0.000	Yes
PE→BI	0.049	0.062	0.780	0.218	No
SI→BI	0.151	0.072	2.092	0.018	Yes
UB→DC	0.064	0.059	1.095	0.137	No
UB→ISU	0.040	0.045	0.899	0.184	No

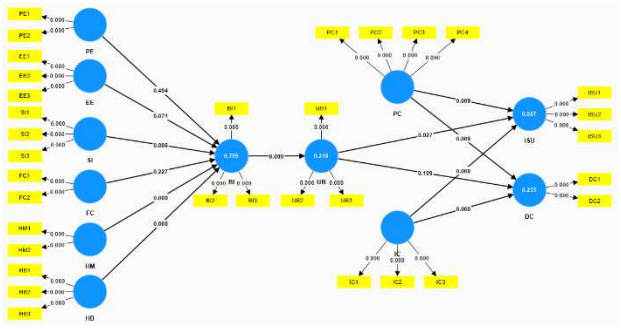

Fig. 2 Bootstrapping result

With respect to the determinants of Behavioral Intention (BI), the results reveal a clear distinction between predictors that retain explanatory relevance in the generative AI context and those that do not. Three hypotheses, namely H1, H2, and H4, are not supported, as indicated by low t-statistics (0.684, 1.809, and 1.209, respectively) and non-significant p-values. These findings suggest that performance expectancy, effort expectancy, and facilitating conditions no longer function as primary drivers of intention, marking a departure from traditional UTAUT2 patterns. This shift is consistent with the broader structural results, indicating that generative AI has reached a level of accessibility and intuitive usability that reduces users' reliance on evaluative judgments when forming intentions.

In contrast, H3 (SI→BI), H5 (HM→BI), and H6 (HB→BI) are all supported. Hedonic motivation and habit exhibit particularly strong effects, with t-values of 4.606 (p = 0.000) and 7.441 (p = 0.000), respectively, while social influence also demonstrates a significant positive effect on intention (t = 2.749, p = 0.006). Collectively, these results indicate that behavioral intention to use generative AI is shaped primarily by motivational, social, and routine-based factors, reflecting the embedded nature of the specific technology in everyday academic practice.

The transition from intention to behavior is reflected in H7 (BI→UB), which is strongly supported with a high t-value of 9.392 (p = 0.000). Although the standardized coefficient is moderate in magnitude, the hypothesis test confirms that intention remains a significant predictor of actual usage frequency. This finding indicates that intention does translate into action, although actual use behavior is also likely influenced by contextual or situational factors beyond the scope of the present model.

A different pattern emerges when examining ethical-use outcomes. For H8 (UB→ISU), the effect is statistically significant (t = 2.216, p = 0.027), whereas H9 (UB→DC) is not supported (t = 1.603, p = 0.109). These results suggest that frequency of use may relate modestly to certain aspects of ethical sensitivity but does not reliably predict disclosure behavior. In contrast, all institutional hypotheses are supported. Policy clarity demonstrates significant effects on both Integrity Safe-Use (ISU) (t = 2.604, p = 0.009) and Disclosure (DC) (t = 2.599, p = 0.009), while integrity culture exhibits particularly strong effects on ISU (t = 13.161, p = 0.000) and a robust influence on DC (t = 6.816, p = 0.000).

The significance patterns across H1–H13 therefore validate the model's conceptual separation between intention formation, behavioral enactment, and ethical engagement, providing strong statistical support for the extended theoretical framework examined in this study.

3.2.4 Model Refinements

The structural results further indicate that the direct paths from actual Use Behavior (UB) to the ethical-use constructs,

namely Integrity Safe-Use (ISU) and Disclosure (DC), are either weak or statistically non-significant. This pattern suggests that frequency of use does not operate as a meaningful causal mechanism for ethical engagement, which is more plausibly grounded in institutional norms, policy expectations, and shared academic values than in experiential familiarity alone. Accordingly, the final model as shown in Fig. 3 conceptually separates the adoption and ethical-use processes into two distinct but coherent pathways.

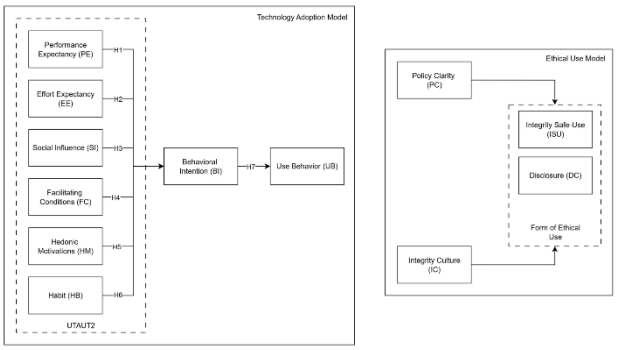

Fig. 3 Refined conceptual framework

The adoption pathway is driven primarily by motivational and habitual factors that shape behavioral intention and subsequent use, whereas the ethical-use pathway is governed directly by institutional conditions, including policy clarity and integrity culture. By excluding unsupported links and weak direct effects from use behavior to ethical outcomes, the refined model offers a clearer representation of how generative AI is both adopted and ethically governed in academic settings. This separation highlights a key theoretical implication: while adoption processes unfold at the individual level through intention and habit formation, ethical engagement is shaped independently through institutional signals rather than emerging as a downstream consequence of usage frequency.

4 Discussion

4.1 Interpretation of Key Findings

4.1.1 Weakening of Evaluative Predictors in a Mass Adoption Environment

A key finding of this study is the non-significance of performance expectancy (PE), effort expectancy (EE), and facilitating conditions (FC) in predicting behavioral intention. This pattern is consistent with prior research suggesting that evaluative cognitive determinants in UTAUT-based models are most influential during early stages of technology adoption but tend to weaken as technologies become familiar and routinely used [14, 28]. In post-adoption contexts, users' perceptions of usefulness, ease of use, and access conditions often converge, thereby reducing the variance necessary for these constructs to meaningfully explain intention.

Within the context of generative AI, the high level of accessibility and intuitive interaction appears to place many academic users in a post-adoption phase despite the relative novelty of the specific technology. Consequently, PE, EE, and FC remain conceptually relevant but no longer function as discriminative predictors of intention. This interpretation demonstrates that once usage becomes routine, the influence of intention on subsequent behavior is constrained by habit [29]. These findings support critiques regarding UTAUT2 by showing that under conditions of widespread familiarity, intention formation is shaped less by evaluative judgments and more by stabilized usage patterns and social context.

In contrast, social influence (SI), hedonic motivation (HM), and habit (HB) remain significant and meaningful predictors of behavioral intention. This

indicates that generative AI use in academic settings is shaped more by social expectations, intrinsic engagement, and automatic behavioral processes. The significance of social influence suggests that the diffusion of generative AI within academic communities has created normative conditions in which its use is socially reinforced, even after the technology has become widely accessible [14]. Strong effects of hedonic motivation and habit suggest that generative AI has become embedded in everyday academic activity. Consistent with habit formation theory [32], use is often triggered by contextual cues within the academic environment, reducing the strength of the intention-behavior link. This shows that generative AI has gradually transformed from a discretionary tool into a routine cognitive resource. Although intention continues to predict actual use, the magnitude of this effect is modest, reflecting a partial decoupling of intention and action in settings dominated by habitual processes. Classical behavioral models assume intention as the primary antecedent of action [31], yet recent research on AI adoption emphasizes that as technologies become routinized, behavior increasingly operates below the level of conscious deliberation [32]. These findings suggest that reinforcing intentions alone is unlikely to substantially alter generative AI use.

4.1.2 Mismatch Between Habitual Usage and Uncertain Ethics

The finding that actual Use Behavior (UB) does not meaningfully predict Integrity Safe-Use (ISU) or Disclosure (DC) challenges the assumption that repeated interaction with generative AI naturally fosters ethical competence or transparency. Prior studies show that increased exposure often accelerates functional reliance without strengthening ethical reasoning or disclosure norms [33-34]. Frequent use may normalize practices with ambiguous ethical status, particularly when guidance is fragmented or implicit. Studies examining early institutional responses to generative AI have documented substantial uncertainty among students and educators regarding when and how AI use should be disclosed, even in environments where such tools are widely used [11].

Emerging research further indicates that disclosure behavior is shaped less by experience and more by perceived social meaning and reputational risk. Students may avoid disclosure not because they view it as unethical, but because disclosure lacks a stable interpretive frame and may signal reduced competence or academic effort [33]. In the absence of explicit disclosure conventions, AI use becomes pragmatically accepted yet ethically under-articulated, creating a gap between practice and accountability [34]. These findings explain why ethical engagement with generative AI does not arise organically through habitual use. It also explains why UB fails to function as a meaningful predictor of ISU or DC without clearly articulated institutional norms that legitimize responsible use and transparency.

4.1.3 Institutional Factors as Key Determinants of Ethical Behavior

The strong influence of policy clarity and integrity culture observed in this study reflects a broader understanding of academic integrity as an institutional rather than an individual phenomenon. Prior research conceptualizes integrity not merely as personal moral compliance, but as an ecosystem shaped by formal rules, informal norms, and organizational signals

[35]. In the context of emerging technologies, ethical behavior is unlikely to develop in the absence of clear governance structures, as users lack stable reference points for responsible practice [18]. This perspective is consistent with recent international guidance emphasizing that generative AI adoption in education has outpaced the development of enforceable and clearly articulated institutional policies [16]. Together, these studies support the interpretation that ethical and transparent use of generative AI is anchored in institutional design and cultural reinforcement, rather than arising naturally from individual experience or frequency of use.

4.2 Multigroup Findings and Analysis

Multigroup Analysis (MGA) was conducted to examine differences in Generative AI adoption and ethical use across respondents subgroups. It reveals how behavioral mechanisms vary by demographic, generational, and institutional context beyond the general structural model.

4.2.1 Universal Adoption Across Demographic Groups

Generative AI has diffused widely across higher education, with 97.4% of respondents reporting prior use and high-intensity usage observed among both students (80.6%) and lecturers (74.5%). These figures indicate that Generative AI is now commonly embedded in everyday academic activities rather than perceived as a novel or optional tool. Importantly, no meaningful differences in usage levels are observed between respondents located inside and outside the metropolitan region, suggesting broadly comparable access and engagement across geographic contexts.

At the same time, similar levels of adoption do not imply uniform governance conditions. Respondents from institutions in the Greater Jakarta area report slightly higher levels of policy clarity and ethical-use behaviors. Although these differences are modest and should be interpreted cautiously, they point to variation in institutional capacity to communicate and support ethical expectations. Overall, the findings suggest that while Generative AI adoption has largely converged across regions, institutional arrangements related to ethical guidance may still differ to a limited extent.

4.2.2 Gaps in Policy Awareness and Institutional Communication

One of the most salient multigroup findings concerns users' awareness of institutional Generative AI policies. Despite near-universal adoption, only 30.5% of respondents report being familiar with the existence and content of Generative AI guidelines. A role-based comparison further shows that while 51% of lecturers indicate clear understanding of institutional policies, most students (52%) report having only heard of such policies without knowing their substance. This gap points to a disconnect between formal governance instruments and their penetration into everyday academic practice.

This pattern reveals a structural limitation of institutional governance that adoption metrics alone cannot capture. Although policy clarity predicts ethical behavior significantly at the structural level, the multigroup analysis indicates that its potential influence is constrained by uneven policy literacy across user groups. In practice, institutional guidelines cannot shape behavior if they do not enter users'

routine decision-making processes. This finding is consistent with evidence that policies have limited impact when they remain peripheral to everyday workflow [11].

Consequently, students rely more on informal cues than formal guidance when using generative AI, which helps explain inconsistent disclosure despite the presence of institutional policies. This pattern reflects an implementation gap where policy existence fails to translate into practical ethical reference points.

4.2.3 Generational Ethics Differences

Across generational groups, the findings reveal a pattern in which Gen Z respondents demonstrate strong adoption metrics but comparatively weak ethical alignment. Their comfort with automation and cognitive offloading reflects their familiarity with digital tools, but this fluency does not translate into higher integrity or disclosure. Instead, Gen Z users report notably lower ethical-use scores than older respondents. This contradiction challenges the assumption that digital proficiency naturally produces ethical maturity. It also highlights psychological processes related to self-presentation and identity: younger users may perceive disclosure as a threat to academic legitimacy or competence, a tendency reinforced by competitive academic environments. Older respondents (Gen X/Y), mostly lecturers, exhibit the inverse pattern: lower intensity of use but higher ethical alignment. Their greater willingness to acknowledge Generative AI use appears linked to a more established professional identity, one less dependent on perceptions of capability or academic comparison.

4.2.4 Policy Awareness in Predicting Ethical Behavior

The multigroup results indicate that policy awareness plays a central role in shaping ethical behavior across respondent groups. Individuals who understand their institution's Generative AI guidelines consistently exhibit higher integrity-safe use and a greater willingness to disclose their Generative AI involvement. In contrast, respondents who are unaware of existing policies, or who possess only a vague understanding of their content, demonstrate the lowest levels of ethical alignment. These patterns suggest that institutional policies and guidelines are not inherently ineffective; however, the presence of formal rules alone, regardless of how clearly they are written, does not automatically translate into ethical practice [36-37].

The findings indicate that the critical mechanism is policy literacy. Users must not only be aware that guidelines exist but also understand their meaning and relevance to academic work. When this cognitive link is absent, policies remain peripheral to everyday decision-making, allowing informal habits and peer norms to dominate. This pattern aligns with theories of norm internalization, which argue that formal rules exert behavioral influence only when they are perceived as legitimate, intelligible, and practically applicable within a given institutional context [38]. In short, the evidence shows that policies and guidelines can meaningfully shape ethical Generative AI use, but only when they are communicated and integrated in ways that make them understandable, accessible, and actionable in daily academic practice.

4.2.5 Disciplinary and Institutional Differences

The multigroup results show that generative AI adoption does not differ substantially between STEM and non-

STEM respondents or between public and private universities, with consistently high adoption across all groups. However, differences emerge in how generative AI is understood and ethically integrated into academic practice. STEM respondents report slightly higher usage intensity and stronger habitual use, reflecting task-related demands. Similarly, while adoption levels are comparable, respondents from public universities demonstrate greater policy awareness and higher ethical use behavior than those from private institutions. This divergence indicates that ethical engagement depends less on adoption itself than on how effectively institutions communicate and embed policy expectations into everyday academic discourse.

4.3 Theoretical Implications

The findings of this study highlight a fundamental theoretical distinction between the formal existence of institutional guidelines and the formation of stable ethical behavior in generative AI use. In Indonesia, many universities have issued their own institutional guidance, and the Ministry of Education has also released national-level recommendations on responsible AI use in higher education [39]. Despite this growing body of guidance, the behavioral patterns observed in this study indicate that these documents have not yet developed into stable normative frameworks capable of consistently shaping everyday academic practice. Ethical alignment emerges primarily among users who have internalized such guidance, while mere awareness of policy existence is insufficient to sustain ethical use.

This condition situates Indonesian higher education within a broader pattern commonly described in technology governance literature, where legal and regulatory systems tend to lag rapid technological development. Scholars have long observed that law and regulation often respond reactively rather than proactively to technological change, producing periods in which new technologies are widely adopted in the absence of clear, enforceable rules [12,40]. In such contexts, guidance documents proliferate, but they function primarily as advisory instruments rather than binding norms. As a result, their influence depends heavily on voluntary interpretation and individual uptake rather than on institutional enforcement or shared expectations.

When regulation follows rather than precedes practice, emerging norms are often shaped by habitual and informal behaviors formed under conditions of ethical ambiguity [37-38]. While norm-sensitive regulation is often intended to enhance legitimacy, this sequencing can be problematic in the context of disruptive technologies such as generative AI. When regulatory frameworks are derived from practices that emerged under conditions of normative ambiguity, they risk reinforcing informal or ethically inconsistent behaviors rather than correcting them. The findings of this study reflect this dynamic.

Consequently, this study contributes to broader discussions on AI governance by distinguishing between the presence of policy and the presence of normative clarity. When policies exist primarily as advisory texts without regulatory force or structured mechanisms of reinforcement, they do not resolve the normative ambiguity surrounding generative AI use. In rapidly evolving technological contexts, ethical behavior depends not on the availability of policy documents but on whether users are situated within institutional ecosystems that

actively support, communicate, and reinforce internalization.

4.4 Practical Implications

The empirical findings of this study carry important implications for institutions, policymakers, and educators seeking to guide responsible generative AI use in higher education.

4.4.1 Integrity Culture over the Proliferation of Guidelines

A central implication of this study is the limited effectiveness of guidelines in the absence of a supportive integrity culture. Although institutional and national guidance on generative AI use exists, only a minority of users report to understand these documents, while the remainder exhibit lower levels of ethical use and disclosure. This finding reinforces prior work on AI governance, which emphasizes that fairness, accountability, and transparency are not achieved through documentation alone, but require sustained institutional commitment and cultural reinforcement [43]. Consistent with broader ethical governance frameworks, institutions should therefore shift from a compliance-oriented mindset toward cultivating a community-based ethical climate, where expectations surrounding generative AI use are internalized socially rather than enforced administratively.

4.4.2 Disclosure Normalization

The persistently low disclosure rates observed in this study reflect a state of normative ambiguity in which students and lecturers remain uncertain about whether acknowledging generative AI use is expected, risky, or socially disadvantageous. Prior research shows that students often perceive co-authorship with AI as ethically ambiguous rather than clearly acceptable or unacceptable, which contributes to hesitation and concealment [42]. To address this, institutions must formalize disclosure as a routine academic practice rather than an exceptional act. Practical measures include standardized disclosure statements, disclosure fields embedded in assignment submission systems, and transparent examples of acceptable generative AI-assisted work. Normalizing disclosure in this way reduces reputational anxiety and aligns transparency with institutional expectations.

4.4.3 Redesigning Coursework

The findings further suggest that students increasingly rely on generative AI for foundational academic tasks, often as a functional necessity rather than a convenience. This reliance challenges traditional assessment designs that assume independent production as a proxy for learning. Prior research has demonstrated that conventional assignments are becoming less effective in ensuring meaningful learning in AI-rich environments [43]. More recent empirical evidence indicates that sustained reliance on generative AI may also undermine independent thinking, critical reflection, and self-regulated learning when AI use substitutes rather than supports cognitive engagement [4].

In response, institutions must redesign coursework to reinforce cognitive ownership by equipping students with the skills to critically evaluate AI-generated outputs, recognize bias and hallucinations, and determine appropriate contexts for AI use. Such pedagogical shifts align with calls for a community-wide ethical framework for AI in education, in which ethical reasoning and critical judgment are embedded throughout teaching and learning practices rather than

treated as peripheral concerns [8]. Importantly, this transformation requires educators to rethink long-standing pedagogical assumptions and redesign learning experiences that foreground human judgment, interpretation, and originality. Such redesign demands creativity, disciplinary sensitivity, and a deep understanding of how students now interact with information. By focusing on ethical and cognitive competence rather than mechanical compliance, institutions create conditions in which responsible generative AI use can flourish, even within academic environments where habitual adoption is already deeply embedded.

4.4.4 Ethical Capacity Building

Given the near-universal adoption of generative AI and the modest predictive role of behavioral intention, attempts to regulate AI use primarily through restriction or surveillance are unlikely to be effective and may incentivize shadow usage. This observation aligns with global policy responses that have struggled to keep pace with rapid technological development, often oscillating between prohibition and regulatory improvisation [44]. Rather than relying on reactive control mechanisms, institutions should focus on developing ethical and critical capacities among students and educators [15]. By embedding discussions of generative AI ethics within curricula, modeling responsible use through faculty practice, and reinforcing shared academic norms, universities can align governance mechanisms with lived academic practices. Such an approach shifts the focus from controlling technology to cultivating ethical culture, enabling responsible generative AI use even in contexts where formal regulation remains incomplete.

5 Conclusion

This study investigated the adoption and ethical use of generative artificial intelligence in Indonesian higher education by extending the UTAUT2 framework with institutional governance and ethical constructs. The findings show that Generative AI adoption has reached a stage of near-universal diffusion across demographic, disciplinary, and institutional groups. At this stage, traditional evaluative determinants of technology acceptance, such as performance expectancy, effort expectancy, and facilitating conditions, no longer play a decisive role in shaping behavioral intention. Instead, intention is primarily driven by social influence, hedonic motivation, and habit, indicating that Generative AI use has become embedded in routine academic practice rather than guided by deliberate cognitive evaluation.

The study further demonstrates that adoption and ethical engagement follow different logics. While behavioral intention predicts actual use behavior, frequency of use does not explain integrity-safe use or disclosure. Ethical outcomes are shaped mainly by institutional conditions, particularly policy clarity and integrity culture, and only when such guidance is understood and internalized. Multigroup analysis further reveals that high adoption does not ensure ethical practice in the absence of policy literacy and normative clarity. This reflects a broader governance gap under non-binding legal frameworks. Taken together, these findings provide an empirical basis for understanding how legal vacuums shift the burden of ethical Generative AI governance from law to institutions, highlighting that responsible use depends not on experience alone but on institutional environments capable of translating policy into shared academics

norms.

5.1 Research Limitation

This study has several limitations that should be considered when interpreting the findings. The use of cross-sectional self-reported survey data limits the ability to capture the evolving nature of generative AI use, leaving open the possibility of response bias in areas such as disclosure and ethical judgment. The Indonesian higher education context introduces unique structural conditions, including the presence of multiple national and institutional guidelines without binding regulatory force, creating a policy environment that may differ from settings with formalized AI governance. In addition, the model focuses on individual-level factors and does not incorporate organizational or systemic variables which may influence ethical behavior. Finally, while the study offers important insights into adoption and ethical use, it does not directly investigate learning outcomes or cognitive impacts, leaving opportunities for future research.

5.2 Future Work

Future research should examine how integrity culture is internalized, as it emerged as the strongest predictor of ethical generative AI use yet remains underexplored in higher education. Further studies should also investigate how policy literacy develops, which communication strategies effectively translate guidelines into practice, and why widespread use does not lead to greater disclosure. Qualitative and comparative research may clarify how disciplinary traditions and institutional governance models shape ethical boundaries, particularly in contexts where formal regulation is absent.

Funding Statement

The authors received no financial support for the research, authorship, and/or publication of this article.

Consent to Participate

Participation was voluntary, and informed consent was obtained from all participants prior to data collection. All participants were aged 16 years or older.

Ethics Approval

Ethical approval for this study was formally waived by the Research Ethics Committee of the Faculty of Engineering Universitas Indonesia, based on the determination that the research was non-interventional, survey-based, involved no clinical or experimental procedures, posed no more than minimal risk to participants, and did not collect personally identifiable or sensitive personal data. The study was conducted in full accordance with the applicable ethical standards and guidelines of the Research Ethics Committee of the Faculty of Engineering Universitas Indonesia, as well as the principles of the Declaration of Helsinki, including voluntary participation, anonymity, confidentiality, and responsible data handling.

Competing Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Authorship

Irdina Rusyda Kamila Arsil conducted the research, including study design, data collection, analysis, and manuscript preparation. Prof. Muhammad Suryanegara provided supervision, intellectual guidance, and contributed to the interpretation of results and critical revisions of the

manuscript.

Data Availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on request.

Acknowledgment

The author expresses sincere gratitude to all respondents who voluntarily participated in this study and contributed their time and perspectives, which made this research possible.

Consent to Publish

Not applicable.

Clinical trial number

Not applicable.

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