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Academic Cheating with Generative AI in Higher Education: An Extended Model of the Theory of Planned Behavior with Motivational Antecedents

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Abstract. This study proposed and tested an extended model of the theory of planned behavior (TPB) to understand the determinants of academic cheating using generative AI (GenAI). This model integrates intrinsic and extrinsic motivation as antecedents of the core constructs of TPB, namely attitude, subjective norms, and perceived behavioral control, to predict cheating intentions and behavior. Quantitative data were collected from 243 undergraduate students in West Java through a survey and analyzed using confirmatory partial least squares structural equation modeling (PLS-SEM). The model demonstrated satisfactory global fit ($SRMR$ = .045; NFI = .92), supporting the hypothesized structure. The results indicate that the proposed model can explain significant variance in cheating intentions and behavior. Perceived behavioral control proved to be the strongest predictor of cheating intentions. More importantly, both behavioral intention and perceived behavioral control directly and strongly predicted self-reported academic cheating behavior. This study concluded that the extended TPB is a robust framework for this phenomenon, highlighting the dominant role of perceived behavioral control. Its practical implications emphasize the need for institutional interventions focused on reducing the perceived ease and increasing the perceived risk of GenAI misuse to maintain academic integrity.

Keywords: academic dishonesty; artificial intelligence in education; generative AI; motivation; student ethics

Learning in higher education has continuously evolved from the simple transfer of knowledge toward the development of critical, creative, collaborative, and communicative competencies (Khoiri et al., 2021). However, the rapid emergence of generative artificial intelligence (GenAI), such as ChatGPT and similar tools, has transformed how students access, process, and produce information (Du & Alm, 2024). While these technologies offer unprecedented opportunities to enhance learning and productivity, they also raise profound ethical and integrity concerns as they enable new forms of academic dishonesty and

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challenge traditional notions of authorship, effort, and originality in education (M. Nelson, 2025).

Advances in learning methods have significantly improved the interaction between educators and students while also enhancing the overall efficiency of teaching and learning processes. Traditional learning approaches used before the 2000s often encountered several obstacles, Advances in learning methods have significantly improved interaction between educators and students while enhancing the overall efficiency of teaching and learning processes. In contrast to traditional learning approaches used before the 2000s, which were often constrained by limited access to learning materials and slower knowledge dissemination, 21st-century learning environments are characterized by the widespread availability of information (Gayathri Devi et al., 2023).

This shift has generated substantial benefits for both students and lecturers, including easier access to diverse learning resources, rapid dissemination of knowledge, and greater flexibility in independent learning (Shoufan, 2023; Szymkowiak et al., 2021). However, the ease of obtaining and providing information can also introduce challenges. Oviedo-Trespalacios et al. (2023) noted that readily accessible information may be unfiltered or of questionable validity, potentially affecting the quality and credibility of both learning and instruction when critical evaluation and triangulation are lacking.

The GenAI revolution, spearheaded by tools like ChatGPT, has fundamentally changed the landscape of higher education (Du & Alm, 2024). This technology represents a paradigm shift, offering previously unfathomable opportunities to facilitate learning, research, and creativity. Students can utilize GenAI for a variety of purposes, from drafting papers and analyzing complex data to creating innovative learning materials (Cano & Nunez, 2024). Its ability to yield access to data and generate high-quality content has quickly led to its wide-scale adoption among academics (Luo, 2025). However, while these tools enhance productivity, they simultaneously introduce ethical dilemmas that threaten the integrity of academic learning and assessment.

Due to the growing ubiquity of digital technologies, humans continually seek digital innovations to improve accessibility to knowledge. In this pursuit, AI has evolved rapidly over the past decade. OpenAI, founded in 2015, developed a series of large language models—GPT-1 (Radford et al., 2018), GPT-2 (Radford et al., 2019), and GPT-3 (Brown et al., 2020), which eventually led to the public release of ChatGPT in November 2022 (OpenAI, 2022). Since then, ChatGPT and similar tools have become widely recognized by the public, including in Indonesia, for their ability to supply instant information and academic assistance. Besides this, ChatGPT is able to solve various problems in academic circles. Firdaus et al. (2025) conducted a survey on students and found that 75.9% of them agreed with the ease of access to information using AI. In addition, Nathania et al. (2023) reported that 84.7% of students frequently used ChatGPT to complete their weekly assignments and, in some cases, during examinations. However, Stone (2023) cautioned that excessive reliance on AI may negatively impact the development of students' own academic skills, emphasizing the need to pay more attention to academic integrity issues.

GenAI is a double-edged sword despite its immense potential. Its ability to generate coherent text that is indistinguishable from human writing has opened the door to new and more sophisticated forms of academic cheating (Liu et al., 2025). This phenomenon raises serious concerns about academic integrity, a key pillar of education. When students use GenAI to complete assignments, essays, or even research reports without an authentic personal understanding or intellectual effort, the value of their academic credentials is jeopardized. Therefore, there is an inherent tension between GenAI's roles as a learning facilitator and a tool for academic misconduct (A. S. Nelson et al., 2025). Despite growing concern, empirical research on the psychological mechanisms that drive students' misuse of GenAI remains scarce. Addressing this gap requires a theoretically grounded approach capable of explaining intentional or volitional behavior, such as the theory of planned behavior (TPB).

Academic integrity is the main reference for students and lecturers in ensuring success and key standards in education (Gottardello & Karabag, 2022; Mulenga & Shilongo, 2024). It provides a guarantee that someone can be accurately recognized for their expertise. Research by Çelik and Razı (2023) highlighted that AI could strengthen academic integrity by helping prevent and detect violations, such as plagiarism, using tools like Turnitin or Grammarly, which analyze extensive databases of academic content to identify instances of improper quoting or paraphrasing. Beyond detection, the threat of exposure by AI can serve as a deterrent, encouraging students to produce original work (Davis, 2022). Furthermore, AI can be integrated into learning management systems (LMS) to monitor patterns in student submissions, such as sudden increases in writing skill, changes in style, or unusual submission times, which might signal academic dishonesty (Mathrani et al., 2021; Rodrigues et al., 2025).

According to Currie (2023), AI can also increase transparency and fairness in grading, which are important components of academic integrity. By using AI to help evaluate written assignments or coding projects, educators can ensure consistent grading criteria and reduce the potential for bias (Yeo, 2023). While human oversight remains important, AI tools can streamline the evaluation process, especially in large classes, and provide objective insights into student performance (Susnjak, 2023). This fairness can build trust in the academic system and motivate students to maintain integrity in their academic endeavors, knowing that their work will be judged fairly.

Although AI contributes positively to various aspects of higher education, its use also introduces significant risks for academic misconduct. One of the most prominent issues is students' misuse of AI, such as language models like ChatGPT or code generators like GitHub Copilot, to complete assignments, essays, or even research papers without any real effort or comprehension. Tools like these can produce high-quality output in seconds, often indistinguishable from that created by humans, making it difficult for educators to perceive violations (Rudolph et al., 2023). Students may thus be tempted to rely on AI to produce work that appears authentic but lacks originality or personal engagement, violating the principles of academic honesty. In addition, AI-generated content poses significant challenges for traditional plagiarism detection systems, which typically compare submissions to existing databases. Because AI can produce original or synthetically generated text that does not correspond to known sources, such misconduct becomes harder to recognize (Pataranutaporn et al., 2021; Trust et al., 2023). This problem is intensified by the rapid development of GenAI, which often outpaces available detection technologies (K. Wang et al., 2025).

Heavy reliance on AI may hinder students' development of essential academic skills (e.g., reading, writing, analysis, and problem-solving), which ultimately reduces their capacity for independent thinking (N. Wang et al., 2024). As a result, academic credentials may no longer accurately represent a student's actual competence (Bettayeb et al., 2024), undermining institutional credibility and their responsibility to cultivate intellectual and ethical growth (Schiff, 2022). Furthermore, Guilherme (2017) noted that AI misuse is not limited to students; educators may also rely on AI to generate research articles, assessments, or exam materials with minimal oversight, potentially resulting in generic, inaccurate, or ethically questionable outputs. Such practices weaken the authenticity of academic work and diminish the role of human judgment in education. Without clear institutional guidelines and ethical standards, the unchecked use of AI may encourage a culture where efficiency is prioritized over academic integrity (Berendt et al., 2020). Therefore, AI adoption in education requires careful regulation and transparency to ensure responsible and ethical application.

The central problem in this study concerns the broader set of factors that may influence students' engagement in unethical GenAI use. The rise of GenAI introduces multiple psychological, social, and situational drivers (e.g., students' personal attitudes, social expectations, institutional environments, and perceptions of control over the technology) that may shape academic misconduct. Understanding how these factors interact is essential for designing effective prevention and intervention strategies (Al-Mamary & Abubakar, 2025). Without such insight, institutional policies may remain purely reactive and fail to address the root causes of misconduct. To systematically examine these determinants, this study employed the theory of planned behavior (TPB) as its primary framework. TPB is a widely recognized as an effective method to predict planned and intentional behaviors (Ma, 2025). It posits that behavior is best predicted by behavioral intention, which is shaped by three components: attitudes toward the behavior, subjective norms (perceived social pressure), and perceived behavioral control (perception of ease or difficulty in performing the behavior). Since the academic misuse of GenAI typically involves deliberate planning, TPB provides a relevant and robust foundation for analyzing the factors that contribute to this issue.

TPB is often extended to gain a richer understanding of the psychological antecedents that shape human intention and behavior. In the academic context, student motivation plays a crucial role. Therefore, this study integrated concepts from self-determination theory (SDT), namely, intrinsic motivation (driven by internal satisfaction and curiosity) and extrinsic motivation (driven by external rewards, such as grades or recognition), as antecedents to the TPB constructs. It was hypothesized that these motivational factors influence students' attitude (H1–H2) and perceived behavioral control (H3–H4), which in turn affect behavioral intention (H5–H7) and, ultimately, dishonest academic behavior (H8–H9).

Accordingly, this study aimed to: (1) examine the effects of intrinsic and extrinsic motivation on students' attitudes and perceived behavioral control; (2) evaluate the predictive power of attitude, subjective norms, and perceived behavioral control on the intention to undertake GenAI-related academic cheating; and (3) determine how behavioral intention and perceived behavioral control predict self-reported dishonest academic behavior. It extended TPB by integrating motivational factors from SDT, providing theoretical depth and practical guidance for enhancing academic integrity in the digital era.

Research Model and Hypothesis Development

The theory of planned behavior (TPB), developed by Icek Ajzen, is an extension of the theory of reasoned action (TRA). TPB is designed to predict behaviors that are not fully under an individual's volitional control by adding the construct of perceived behavioral control (PBC) (Rodrigues et al., 2025; Roe & Perkins, 2022). It has proven to be a very powerful and parsimonious framework in predicting a wide range of behaviors across various domains, including health, environmental, and economic (Bin-Nashwan et al., 2023). In recent years, TPB has also been successfully applied to predict various forms of academic cheating, demonstrating its relevance in the context of educational ethics (Perkins, 2023).

According to TPB, the immediate antecedent of behavior is behavioral intention, which reflects one's readiness and motivation to act. Intention itself is determined by three main constructs (Cotton et al., 2024; Rasul et al., 2024; Yeo, 2023). The first one is attitude toward the behavior, which refers to an individual's positive or negative evaluation of the implementation of a particular behavior. This attitude is shaped by the individual's beliefs about the behavior's potential consequences (behavioral beliefs). In the present context, attitudes will reflect whether a student views cheating with GenAI as beneficial, acceptable, or otherwise. Then there are subjective norms, which are an individual's perception of social pressure from significant others (e.g., peers, lecturers, family) to perform or not perform the behavior. Subjective norms are derived from normative beliefs about what is expected by others. Lastly, perceived behavioral control reflects one's perception of their ability to successfully perform a behavior, encompassing beliefs about internal (e.g., skills, knowledge) and external (e.g., opportunities, resources, barriers) factors that may facilitate or hinder it. In the context of GenAI fraud, this may include the individual's perceptions about their technical ability to use the tool and the likelihood of going undetected.

Within TPB, perceived behavioral control is understood as an important predictor of both behavioral intention and actual behavior. Its effect on behavior tends to be stronger when perceived control aligns with real situational control. For instance, a student may intend not to cheat, yet if an opportunity arises in a low-supervision environment, their likelihood of cheating increases because actual control facilitates it (Cronan et al., 2018; Yusuf et al., 2024).

To further explain why students develop particular attitudes, subjective norms, and perceptions of control toward GenAI use, this study extended the TPB framework by incorporating motivational constructs from self-determination theory (SDT). SDT differentiates between intrinsic motivation (engaging in an activity for inherent satisfaction) and extrinsic motivation (engaging in an activity to achieve external outcomes like high grades or avoidance of penalties) (Annamalai et al., 2025). In the academic setting, these motivational orientations can shape how students interpret the usefulness, acceptability, and ethical implications of GenAI use.

Students who are predominantly extrinsically motivated tend to focus on outcomes (e.g., high grades, early graduation) (Kotera et al., 2023). For these students, GenAI can be viewed as an efficient tool to achieve these goals, even if it means taking unethical shortcuts. Therefore, extrinsic motivation is expected to foster more positive or permissive attitudes toward cheating (Khern-am-nuai et al., 2018).

Furthermore, external pressure to achieve can make students think that using any available means is a controlled, necessary action.

In contrast, students with high intrinsic motivation find satisfaction in the learning process itself (Kotera et al., 2023) and tend to value in-depth understanding and skill development. Based on this perspective, using GenAI for cheating will undermine the primary goal of education, which is authentic learning. Therefore, intrinsic motivation is expected to foster negative attitudes toward cheating (Annamalai et al., 2025). Intrinsically motivated students also tend to have higher self-efficacy in academic tasks, which may increase their perception of their ability to succeed without cheating.

TPB provides the main foundation for this study because academic cheating is understood as a deliberate, planned behavior rather than a spontaneous act. According to TPB, behavior is primarily determined by an individual's behavioral intention, which in turn is shaped by three psychological determinants: attitude, subjective norms, and perceived behavioral control (Ma, 2025). A student who holds a favorable evaluation of cheating with GenAI, perceives that peers also engage in such practices, and believes that cheating is easy to execute and difficult to detect is more likely to form a strong intention to cheat (Jiao & Cao, 2024). Intention then becomes the most proximal antecedent of actual behavior.

In addition, TPB posits that perceived behavioral control may also directly influence behavior, particularly when it reflects actual opportunities or constraints (Yusuf et al., 2024). In contexts where monitoring is weak or technical barriers are low, students who feel capable of cheating may proceed even if their intention is weak. Based on the core TPB relationships, the following hypotheses were proposed:

H1: A more positive attitude toward academic cheating with GenAI will positively and significantly influence behavioral intention.

H2: A higher subjective norm will positively and significantly influence behavioral intention.

H3: A higher perceived behavioral control will positively and significantly influence behavioral intention.

H4: Behavioral intention will positively and significantly influence self-reported dishonest academic behavior.

H5: Perceived behavioral control will positively and significantly influence self-reported dishonest academic behavior.

Although TPB explains the proximal predictors of intention and behavior, it does not fully explain why students develop particular attitudes and perceptions of control in the first place. To address this theoretical gap, this study incorporated motivational orientations from SDT as background factors influencing attitude and perceived behavioral control.

SDT distinguishes between intrinsic motivation (engaging in activities out of inherent interest or satisfaction) and extrinsic motivation (engaging in activities to obtain rewards or avoid penalties) (Annamalai et al., 2025). These motivational orientations shape how students evaluate the use of GenAI and how much control they perceive having over their academic actions. Thus, intrinsic and extrinsic motivations serve as underlying antecedents that feed into the TPB components, so based on these

arguments, the study proposes the following hypotheses:
H6: Extrinsic motivation will positively and significantly influence attitude toward academic cheating with GenAI.
H7: Intrinsic motivation will negatively and significantly influence attitude toward academic cheating with GenAI.
H8: Extrinsic motivation will positively and significantly influence perceived behavioral control.
H9: Intrinsic motivation will negatively and significantly influence perceived behavioral control.

The extended model integrates SDT and TPB into a unified structure. Intrinsic and extrinsic motivation operate as background factors influencing the TPB constructs of attitude and perceived behavioral control, which, together with subjective norms, shape behavioral intention. Intention, along with perceived behavioral control, then ultimately predicts self-reported dishonest academic behavior. In summary, the model positions TPB as the primary explanatory mechanism and SDT as the secondary foundation that clarifies the motivational origins of TPB's proximal predictors.

Methods

This study employed a quantitative design with a cross-sectional survey approach. The primary focus was on students studying at various universities in West Java Province, Indonesia.

Participant Description

The sampling technique used was purposive sampling, with the following selection criteria: (1) active students of universities in West Java; (2) second- to fourth-year students; (3) non-diploma students; and (4) majors in science, education, social sciences, and humanities. Participants were recruited through online survey links distributed via university mailing lists, faculty WhatsApp groups, and student academic forums. Data were collected from January to April 2025. The research protocol was reviewed and approved by the Research Ethics Committee of Physics Education at Islamic State University (UIN) Sunan Gunung Djati Bandung. The researchers obtained 243 respondents, whose detailed demographic characteristics are shown in Table 1.

Table 1

Detailed Description of Research Participants

Characteristic	Category	*N*	Percentage (%)
Gender	Male	133	54.7
	Female	110	45.3
Academic year	2nd year	82	33.7
	3rd year	85	35.0
	4th year	76	31.3
Major	Science	64	26.3
	Education	73	30.0

Table 1 (Cpntinued)

Detailed Description of Research Participants (continued)

Characteristic	Category	*N*	Percentage (%)
	Social sciences	48	19.8
	Humanities	58	23.9
Frequency of GenAI usage	Daily	194	79.8
	Weekly	32	13.2
	Monthly	15	6.2
	Rarely	2	0.8

The G*Power application was used to determine the minimum number of participants needed for the study, with an average effect size of .15, a maximum acceptable error margin of .05, a power level of .95, and four predictors, resulting in a minimum sample size of 129. All participants gave informed consent prior to data collection in accordance with research ethics. All participants gave informed consent prior to data collection in accordance with research ethics. Participation was entirely voluntary, without any form of coercion or incentives. No personally identifiable information was collected; only general demographic data, including gender, academic year, and major, were recorded to support sample description.

Instruments

All items were adapted from prior studies (Al-Qaysi et al., 2024; Chen et al., 2025; Julián & Bonavia, 2020; Ma, 2025) and modified slightly to fit the research context of GenAI use in academic settings. Items were rated on a 9-point Likert scale ranging from 1 (Strongly Disagree) to 9 (Strongly Agree), providing a more detailed response spectrum for analysis. The questionnaire included measures of attitude (At), subjective norms (SN), perceived behavioral control (PBC), behavioral intention (BI), intrinsic motivation (IM), extrinsic motivation (EM), and academic dishonesty (AD), as summarized in Table 2.

Table 2

Validity and Reliability of Research Instruments

Construct	Source	Operational definition	Item example	α	CR	AVE
Intrinsic motivation (IM)	Chen et al. (2025); Renfeng et al. (2025)	Internal drive derived from curiosity, satisfaction, and enjoyment in the learning process.	I enjoy experimenting with GenAI even when there is no pressing need or external reward.	.877	.924	.802
Extrinsic motivation (EM)	Chen et al. (2025); Renfeng et al. (2025)	Motivation driven by external factors such as grades, performance outcomes, or others' expectations.	I use AI tools because they provide solutions faster than working without them.	.873	.900	.753

Table 2 (Continued)

Validity and Reliability of Research Instruments (continued)

Construct	Source	Operational definition	Item example	α	CR	AVE
Attitude (AT)	Al-Qaysi et al. (2024); Sallam et al. (2024)	Individual positive or negative evaluation of academic cheating behavior involving GenAI.	Using GenAI to complete assignments without engaging in learning is acceptable.	.781	.843	.645
Subjective norms (SN)	Hsiao and Tang (2024); Ivanov et al. (2024)	Perceived social pressure from significant others to engage or not engage in academic misconduct.	Most of my friends believe that using GenAI to complete assignments is normal.	.742	.848	.653
Perceived behavioral control (PBC)	Ma (2025)	Perceived ease or difficulty of committing academic fraud using GenAI, including confidence in avoiding detection.	I am confident I can use GenAI for assignments without the lecturer knowing.	.783	.859	.672
Behavioral intention (BI)	Wu et al. (2025)	Motivational readiness and commitment to engage in academic cheating using GenAI.	I intend to use GenAI for assignments next semester even though it is prohibited.	.803	.882	.714
Academic dishonesty (AD)	Julián and Bonavia (2020)	Self-reported engagement in unethical academic practices using GenAI.	In the last semester, I submitted assignments generated by GenAI as my own work.	.733	.844	.645

The original English-language instruments were adapted for application within an Indonesian higher education context. The adaptation process employed a forward–backward translation procedure to ensure both conceptual and linguistic equivalence between the original and translated versions. Three bilingual experts independently reviewed the translated items to ensure cultural appropriateness and clarity.

A pilot test involving 30 undergraduate students was conducted to assess comprehension, clarity, and reliability before full implementation. Minor revisions were made to wording for readability without altering the construct meanings. Formal permission to use and adapt the cited scales was obtained from the corresponding authors when required, and the adapted items may be reused for future academic research with proper attribution.

Data Analysis

Data were analyzed using partial least squares structural equation modeling (PLS-SEM) with SmartPLS version 4. This approach was chosen because it is suitable for predictive modeling and theory testing involving complex models with multiple latent constructs (Ringle et al., 2024). All observed variables were treated as continuous indicators. Prior to analysis, data screening was conducted to assess missing values and distributional characteristics. No missing data were identified (0.0%), as the online survey platform required complete responses before submission.

Univariate skewness and kurtosis values for all indicators fell within ±1.5, indicating acceptable univariate normality and supporting the approximate distributional assumptions required for PLS-SEM estimation (Hair et al., 2021). Descriptive statistics, including means and standard deviations, were calculated to assess the central tendency and dispersion of responses. The PLS-SEM analysis was conducted in two stages: (1) measurement model evaluation, including reliability, convergent validity, and discriminant validity; and (2) structural model evaluation, examining path coefficients, coefficient of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2). Bootstrapping with 5,000 resamples was used to assess the significance of path estimates.

Results

This research began by processing the descriptive statistics to find the results of standard statistics. Descriptive statistics are important because they simplify large, complex datasets into clear and manageable summaries, allowing scholars to understand the "big picture" at a glance (Brownstein et al., 2019). By organizing raw data and calculating simple measures like averages or ranges, the researchers could identify patterns and trends that would be impossible to spot in a chaotic list of numbers, serving as the essential foundation for making informed decisions and communicating findings effectively. The descriptive statistics can be seen in Table 3.

Table 3

Descriptive Statistics

Variable	Mean	Median	Min	Max	SD
Intrinsic motivation	14.60	15	5	25	4.62
Extrinsic motivation	15.28	16	3	26	4.45
Attitude	14.70	15	3	26	4.42
Subjective norms	14.88	15	4	27	4.53
Perceived behavioral control	15.13	15	3	25	4.42
Behavioral intention	15.23	15	5	27	4.61
Academic dishonesty	15.07	15	5	26	4.29

The descriptive statistics reveal a highly consistent pattern of central tendency and dispersion across all constructs. As detailed in Table 3, the mean scores for all variables were clustered within a narrow range, with extrinsic motivation recording the highest average (M = 15.28, $STDEV$ = 4.45) and intrinsic motivation the lowest (M = 14.60, $STDEV$ = 4.62). The close alignment between the mean and median values, with most medians being 15, apart from extrinsic motivation at 16, suggested that the data for each variable were relatively symmetrically distributed. Furthermore, the variability in participant responses was uniform across measures, as indicated by standard deviations ranging consistently between 4.29 and 4.62. Academic dishonesty, specifically, showed moderate prevalence (M = 15.07, $STDEV$ = 4.29), falling centrally within the observed minimum to maximum range of 5 to 26.

Systematic error variance, or what can also be called common method bias (CMB), occurs when measurements are obtained from the same source or method, which can distort the relationship between constructs (Hair et al., 2021). This bias can inflate or deflate the observed relationship between variables, triggering misleading conclusions (N. Kock, 2015). Detecting and controlling CMB is very important in SEM research, because controlling it will ensure the validity of research findings (F. Kock et al., 2021). To assess potential CMB in the current study, the full collinearity assessment method was applied (N. Kock, 2015). In this approach, variance inflation factor (VIF) values are examined to detect both vertical and lateral collinearity, which may indicate CMB contamination. Table 4 shows the CMB analysis results. See Table 4

Table 4

CMB Analysis Results Through VIF Observation

Exogenous variable	Endogenous variable	VIF
Intrinsic motivation	Attitude	1.038
Extrinsic motivation	Attitude	1.038
Intrinsic motivation	Perceived behavioral control	1.144
Extrinsic motivation	Perceived behavioral control	1.144
Attitude	Behavioral intention	1.328
Subjective norms	Behavioral intention	1.224
Perceived behavioral control	Behavioral intention	1.203
Behavioral intention	Academic dishonesty	1.112
Perceived behavioral control	Academic dishonesty	1.008

All VIF values in this study ranged between 1.008 and 1.328, well below the conservative threshold of 3.3, suggesting that multicollinearity and CMB were not a concern. This indicates that the observed associations among constructs primarily reflect substantive rather than artifactual relationships (N. Kock, 2015). The results showed that the variance explained by a single factor or by shared method effects is minimal. Obtaining the VIF value validates the reliability of the SEM measurement model employed in the study, thus confirming that the relationships between constructs, such as intrinsic motivation, extrinsic motivation, subjective norms, perceived behavioral control, and behavioral intentions, are not artificially inflated by the measurement method used (N. Kock & Dow, 2025). The absence of CMB strengthens the credibility of the conclusions made regarding the TPB constructs and their influence on academic dishonesty involving GenAI. Collectively, these findings support the conclusion that the observed effects reflect substantive conceptual relationships rather than artifacts of the data collection process (Jordan & Troth, 2020).

Discriminant validity was assessed using the heterotrait–monotrait ratio (HTMT), following the recommendations of Henseler et al. (2015). All HTMT ratios ranged from .061 to .237, well below the recommended cutoff of .85, confirming that each latent construct (attitude, subjective norms, perceived behavioral control, intrinsic and extrinsic motivation, and academic dishonesty) captures a unique theoretical dimension. These results indicate that the constructs are empirically distinct and that the measurement model demonstrates adequate discriminant validity. The detailed HTMT matrix is presented in Table 5.

Table 5

HTMT Matrix Results

Construct	AD	At	BI	EM	IM	PBC	SN
AD	–						
At	.170	–					
BI	.167	.094	–				
EM	.142	.096	.113	–			
IM	.061	.237	.089	.208	–		
PBC	.169	.171	.131	.123	.127	–	
SN	.171	.154	.138	.212	.100	.121	–

Note. AD = academic dishonesty; At = attitude; BI = behavioral intention; EM = extrinsic motivation; IM = intrinsic motivation; PBC = perceived behavioral control; SN = subjective norms.

As shown in Table 5, all heterotrait–monotrait (HTMT) ratios were below the recommended threshold, confirming adequate discriminant validity among the study constructs (Henseler et al., 2015). This supports the theoretical structure of the TPB framework and ensures that each latent variable captures a distinct conceptual domain. Consequently, the structural relationships among attitude, subjective norms, perceived behavioral control, motivational constructs, and GenAI-related academic dishonesty can be interpreted with confidence, as they are not confounded by overlapping measurements.

The results of the coefficient of determination (R2) obtained in this study can be seen in Table 6.

Table 6

Coefficient of Determination (R^2) Results

Endogenous variable	R^2
Attitude	.412
Perceived behavioral control	.444
Behavioral intention	.622
Academic dishonesty	.573

The explanatory power of the model was assessed using the coefficient of determination (R^2) for each endogenous construct. The model explained 41.2% of the variance in attitude, 44.4% in perceived behavioral control, 62.2% in behavioral intention, and 57.3% in academic dishonesty. Following the criteria proposed by Hair et al. (2021), these R^2 values indicate moderate-to-substantial explanatory power, suggesting that the extended TPB framework integrating intrinsic and extrinsic motivation as antecedents adequately captures the key psychological mechanisms underlying GenAI-related academic cheating behavior.

The structural model was then evaluated through path coefficient analysis and bootstrapping with 5,000 resamples, ensuring the reliability and stability of the estimates Hair et al. (2021). Detailed results of the structural model assessment are presented in Table 7 and visualized in Figure 1.

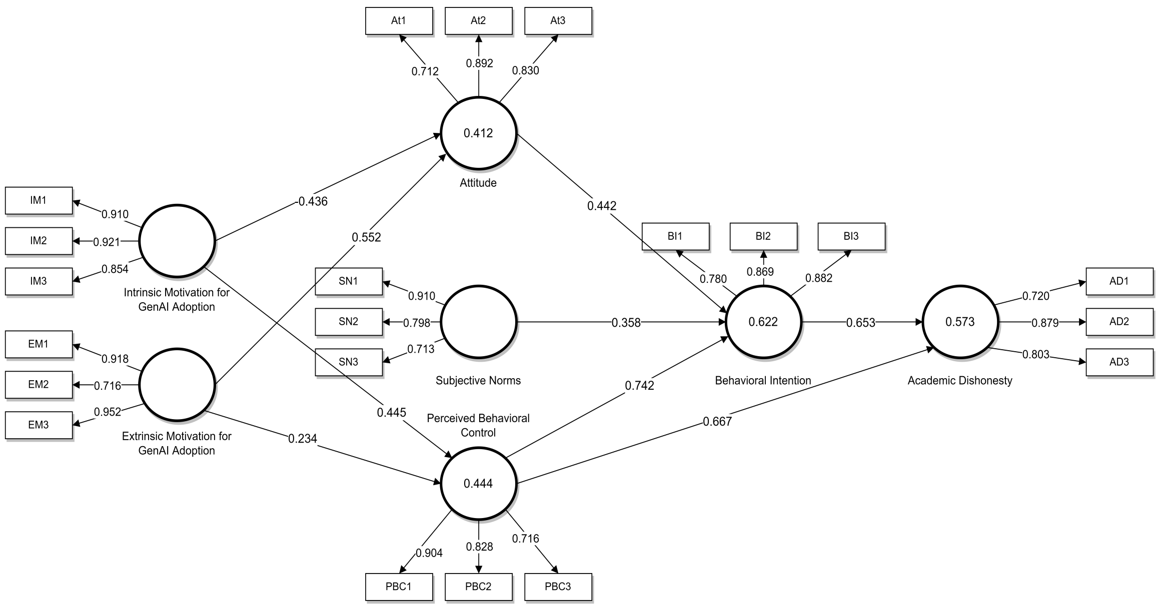
Table 7

Structural Model Assessment Results

H	Path	Beta	*t* value	*p* value	f^2	Remarks
H1	Extrinsic motivation → Attitude	.552	3.472	.001	.223	Accepted
H2	Intrinsic motivation → Attitude	-.436	4.449	.000	.263	Accepted
H3	Extrinsic motivation → Perceived behavioral control	.234	3.642	.000	–	Accepted
H4	Intrinsic motivation → Perceived behavioral control	.445	3.654	.000	–	Accepted
H5	Attitude → Behavioral intention	.442	3.488	.001	–	Accepted
H6	Subjective norms → Behavioral intention	.358	4.552	.000	–	Accepted
H7	Perceived behavioral control → Behavioral intention	.742	4.213	.000	–	Accepted
H8	Behavioral intention → Academic dishonesty	.653	3.836	.000	–	Accepted
H9	Perceived behavioral control → Academic dishonesty	.667	3.778	.000	–	Accepted

Figure 1

Structural Model Assessment Results



All hypothesized paths (H1–H9) were statistically significant ($p < .01$), with standardized path coefficients ranging from $\beta = .23$ to $\beta = .74$. Perceived behavioral control showed the strongest influence on behavioral intention ($\beta = .74$, SE = .09, 95% CI [.57, .87]), followed by its direct effect on academic dishonesty ($\beta = .67$, *SE* = .11, 95% *CI* [.44, .83]). Behavioral intention also had a substantial direct effect on academic dishonesty ($\beta = .65$, SE = .10, 95% *CI* [.46, .81]).

Bootstrapped indirect effects confirmed that behavioral intention partially mediated the relationship between perceived behavioral control and academic dishonesty, denoting that students' perceived control both directly and indirectly shaped their dishonest behaviors. The global model fit indices demonstrated adequate fit (*SRMR* = .045; *NFI* = .92), supporting the robustness of the proposed extended TPB model. These findings underscore the central role of perceived behavioral control in influencing both the intention and execution of GenAI-related academic cheating, while also validating the theoretical integrity of the model.

Interestingly, extrinsic and intrinsic motivations exerted opposite effects on attitude. Extrinsic motivation had a significant positive influence (β = .552, p = .001, f^2 = .223), suggesting that external drivers (e.g., rewards, recognition) enhance positive attitudes towards cheating. In contrast, intrinsic motivation showed a significant negative effect (β = -.436, p < .001, f^2 = .263), indicating a more complex motivational dynamic where self-driven motivation reduces favorable attitudes toward the behavior under study. Further, both extrinsic (β = .234) and intrinsic motivation (β = .445) positively influenced perceived behavioral control, showing that motivational factors strengthen individuals' sense of command over their actions. Attitude (β = .442) and subjective norms (β = .358) were also significant predictors of behavioral intention, aligning with the TPB framework. Overall, the model demonstrates substantial explanatory power, as illustrated by R^2 values establishing moderate to strong predictiveness: attitude (R^2 = .412), perceived behavioral control (R^2 = .444), behavioral intention (R^2 = .622), and academic dishonesty (R^2 = .573). Collectively, the findings confirm the robustness of the SEM-PLS model, with perceived behavioral control and behavioral intention emerging as the most influential constructs driving academic dishonesty.

Discussion

This study aimed to develop and test an extended model of TPB to explain the determinants of academic cheating facilitated by GenAI. The results strongly support TPB as the core explanatory framework, showing that cheating behavior emerges primarily from the combined influence of attitudes, subjective norms, perceived behavioral control, and behavioral intentions. Within this TPB structure, motivational factors from self-determination theory (SDT) were incorporated as antecedents to help explain why students develop certain attitudes and perceptions of control. The findings revealed that intrinsic and extrinsic motivation significantly shape TPB variables—particularly attitudes—thus functioning as upstream psychological drivers rather than central predictors of behavior. Intrinsic motivation was found to reduce permissive attitudes toward GenAI-assisted cheating, consistent with studies showing that students who value genuine learning tend to reject unethical shortcuts (Alotaibi, 2025; Hsiao & Tang, 2024; Nikolic et al., 2024). Conversely, extrinsic motivation was associated with more favorable attitudes toward cheating, indicating that external pressures such as grades or rewards may increase susceptibility to academic misconduct. These results reinforce that interventions seeking to reduce GenAI-related cheating must address not only behavioral regulation (TPB pathways) but also the motivational antecedents that shape students' beliefs and behavioral evaluations.

No post hoc analysis was conducted; all model paths were defined a priori based on the theoretical underpinnings of TPB and SDT, underscoring the confirmatory design and theoretical soundness of the analysis. These results further validate the robustness of the proposed extended TPB framework in predicting academic cheating behavior in a GenAI context.

Interestingly, both intrinsic and extrinsic motivation positively influenced perceived behavioral control. This suggests that motivated students, regardless of their motivational source, tend to feel more capable and confident in using GenAI technology (Yusuf et al., 2024). Intrinsically motivated students may develop deeper mastery of the tool due to curiosity, while extrinsically motivated students may be driven to become proficient in using the tool as an efficient way to achieve their academic goals (Sivasubramaniam, 2025).

In accordance with the TPB framework, all three core components—attitude, subjective norms, and perceived behavioral control—were shown to be significant predictors of behavioral intention to cheat. However, the most striking finding here was the remarkable predictive power of perceived behavioral control, which emerged as the strongest predictor of intention. This implies that in the context of GenAI, the most dominant factor in shaping students' intention to cheat is their belief that they can do so easily and undetected (M. Nelson, 2025; Rasul et al., 2024; Zlotnikova et al., 2025). Ease of access, speed, and difficulty in tracking GenAI usage appear to create a very high perception of control, which directly drives the intention to misuse it (Fošner, 2024).

Attitude and subjective norms also played significant roles, but their effects were smaller compared to that of perceived behavioral control. This suggests that while personal beliefs and peer pressure contribute to cheating intentions, the primary determinants are perceptions of opportunity and ability. If a student believes cheating is easy and not risky, personal beliefs and social norms become secondary considerations (Chiu, 2024; Tzirides et al., 2024).

The results of this study strongly confirm the central role of behavioral intention as a mediator, as hypothesized in H10. The influences of attitude, subjective norms, and perceived behavioral control on academic cheating behavior are largely channeled through intention. The path from intention to academic cheating behavior (H8) also proved highly significant and robust, confirming that BI is a reliable proximal predictor of action (Rasul et al., 2024). However, the most crucial and concerning finding is the very strong direct path from perceived behavioral control to behavior (H9). This suggests that perceived control not only shapes intention but also directly triggers the cheating behavior itself, regardless of pre-existing intentions (Dai, 2025). In other words, the perception that the opportunity to cheat is present, easy, and safe is the most powerful trigger of behavior. This highlights the importance of situational factors, showing that even students who may not have a strong intention to cheat may be tempted to do so if they feel they have complete control and minimal risk (Chan & Lee, 2023; Luo, 2025). Although alternative model configurations—such as reversed causal paths between intention and perceived control—could produce comparable fit, the present specification was retained based on theoretical precedence and parsimony within the TPB framework. Including these variables in future research may provide a more nuanced understanding of academic cheating in the AI era and support the creation of comprehensive, evidence-based prevention strategies.

Intrinsic and extrinsic motivations serve as important antecedents in shaping individual attitudes, particularly in the context of behavioral frameworks such as TPB (Law et al., 2017). Intrinsic motivation driven by internal satisfaction, interest, or a desire to learn may lead to deeper engagement, but may also lead to more critical evaluations of tools such as GenAI when students perceive them as undermining authentic learning (Khan et al., 2023). In contrast, extrinsic motivation rooted in external rewards such as grades or recognition may promote positive attitudes toward GenAI, as students may perceive it as a way to achieve better academic outcomes (Malhotra et al., 2008). In structural modeling, the significance of intrinsic and extrinsic motivation in predicting attitude suggests that these motivational constructs are strong mediators. These motivational orientations affect not only the valence of attitudes (positive or negative) but also their cognitive and affective underpinnings. This mediating role is particularly relevant in education, where students' motivational orientations significantly influence how they interpret the ethical, practical, and academic implications of GenAI use (Luqman et al., 2018). The dual influence also illuminates the need for a balanced educational strategy that fosters intrinsic interest in learning while acknowledging the role of extrinsic incentives in shaping students' acceptance and ethical attitudes toward emerging technologies (Malhotra et al., 2008).

This study offers a theoretical contribution by successfully applying and extending the TPB model to the domain of contemporary technological behavior. The findings particularly underscore the dominant role of perceived behavioral control in contexts where the behavior (in this case, cheating with GenAI) is perceived as low-risk and difficult to detect, suggesting that the relative weight of TPB components may vary depending on the nature of the behavior being studied. Practically, the findings offer several actionable recommendations for higher education institutions. Given that perceived behavioral control exhibited the largest total effect, interventions should primarily aim to reduce students' sense of ease and opportunity regarding the misuse of GenAI. This can be achieved by designing AI-resistant assessment formats (e.g., oral examinations, process-based projects, or real-world case studies) and by emphasizing detection and enforcement mechanisms to increase the perceived difficulty and risk of cheating.

While not the strongest factor, attitude likewise remains an important predictor of cheating behavior. Complementary initiatives should therefore target attitude and subjective norms through integrated ethics-oriented education, AI ethics literacy programs, academic integrity workshops, and transparent institutional policies that promote an integrity-centered learning culture. Classroom discussions, campus-wide campaigns, and codes of conduct that emphasize the value of original work and the consequences of cheating can further help counter permissive subjective norms and foster negative attitudes toward academic dishonesty. Finally, given that intrinsic motivation drives negative attitudes toward cheating, instructors should design engaging and relevant learning experiences that shift students' focus from simply pursuing grades (extrinsic) to enjoying the learning process (intrinsic).

Limitations

This study had several limitations. First, the cross-sectional and self-reported design limits causal inference and external validity, as relationships observed at one point in time may not fully capture the evolving dynamics of GenAI-related behaviors. Future research should therefore employ longitudinal or multigroup SEM approaches to examine model invariance across institutions and track temporal changes in motivation, intention, and behavior.

Second, the reliance on self-reported data might introduce social desirability bias, although participant anonymity was ensured to minimize this risk.

Third, the measurement model may benefit from further refinement and revalidation in future studies, particularly to ensure that all GenAI-related ethical dimensions are comprehensively and consistently operationalized within the TPB framework.

Fourth, the number of samples used is limited to second- to fourth-year students studying in the West Java area, and thus cannot fully represent the broader population. Several biases may have been introduced when participants filled out the questionnaire, for example, by filling it out carelessly or not understanding the meaning of the statements.

Finally, future studies could explore additional moderating variables, such as personality traits (e.g., honesty–humility) or situational factors (e.g., task load), to expand the model's explanatory scope.

Conclusion

This study successfully expanded the theory of planned behavior (TPB) by integrating motivational constructs from self-determination theory (SDT) to explain academic dishonesty facilitated by generative AI (GenAI). The model achieved satisfactory global fit (SRMR = .045; NFI = .92), confirming that the extended TPB structure adequately captured the determinants of GenAI-related cheating behavior. The strength of the path coefficients, particularly from perceived behavioral control (β = .742) and behavioral intention (β = .653), further validates the model's explanatory power and highlights the pivotal role of perceived behavioral control in predicting both intention and behavior. Theoretically, these findings reinforce TPB's predictive mechanism while demonstrating how motivational antecedents from SDT enrich its explanatory depth. Practically, the study provides actionable insights for universities to design interventions that reduce students' perceived ease and opportunity to misuse GenAI. Collectively, the results emphasize that maintaining academic integrity in the digital era requires both structural and motivational strategies grounded in behavioral theory.

The results illustrate that GenAI-related academic dishonesty should be understood not merely as an ethical lapse but as a behavior shaped by students' perceived opportunity, control, and motivational orientation. The dominant role of PBC suggests that when students believe GenAI misuse is easy, accessible, and unlikely to be detected, ethical considerations and social expectations become secondary. This implies that institutional environments implicitly communicate behavioral affordances that can normalize misconduct if left unregulated. At the same time, the contrasting effects of intrinsic and extrinsic motivation indicate that learning climates emphasizing performance outcomes and grades may unintentionally reinforce permissive attitudes toward GenAI misuse, whereas learning-oriented environments foster resistance to unethical shortcuts. Collectively, these findings convey that safeguarding academic integrity in the GenAI era requires a systemic alignment between institutional structures, assessment design, and motivational climates, where reducing perceived ease of misuse and strengthening authentic learning values become central to influencing students' behavioral decision-making processes.

Implications

Despite these limitations, the findings provide several important insights. The results illustrate the dominant role of perceived behavioral control and behavioral intention in driving academic dishonesty, while motivation (extrinsic vs. intrinsic) shapes attitudes and perceived control in opposite but meaningful ways.

The effect size distribution, ranging from small-to-medium (e.g., extrinsic motivation on perceived behavioral control) to large (e.g., perceived behavioral control on intention), further confirms the robustness and nuanced dynamics of the PLS-SEM model.

These results substantiate TPB's predictive mechanism within a GenAI context, while the inclusion of motivational antecedents from SDT adds explanatory depth to the model. No post hoc analysis was required, underscoring the model's theoretical soundness and confirmatory nature.

Recommendations

This study provides several practical implications that can be utilized by higher education institutions, lecturers, policy makers, and educational technology developers in tackling the misuse of GenAI in academic contexts. First, violations of GenAI and ethical awareness directly affect students' level of academic dishonesty, emphasizing the importance of AI literacy as part of the learning curriculum. Educational institutions should therefore develop special training modules that not only teach how to use AI technically, but also explicitly discuss ethical boundaries, institutional rules, and potential negative impacts on academic integrity. Second, the results of this study indicate that attitudinal factors and subjective norms have a major influence on cheating intentions and behavior.

Based on these findings, educational institutions should adopt integrated strategies that address both structural and psychological determinants of GenAI-related academic dishonesty. These strategies should focus on four complementary domains. First, policy and governance interventions are needed to establish explicit AI-use guidelines, codes of academic ethics, and consistent enforcement procedures that reduce students' perceived behavioral control and opportunity to cheat. Active leadership support and transparent sanctions will reinforce accountability and institutional integrity. Second, pedagogical and curricular redesign is needed to develop process-based and critical-thinking assessments, such as oral examinations, project-based evaluations, and personalized assignments. These approaches decrease the feasibility of GenAI misuse while fostering deeper cognitive engagement and authentic learning outcomes. Third, technological safeguards and monitoring, including AI-based detection tools, must be integrated into learning management systems (LMS) to identify suspicious submission patterns and provide formative feedback to both students and instructors. Such systems function as deterrents and early-warning mechanisms against misuse. Fourth, institutions should promote ethical literacy programs, digital citizenship campaigns, and integrity workshops that strengthen intrinsic motivation and pro-academic behavior. Lecturers should model responsible technology use and guide students in understanding both the opportunities and risks of GenAI. As a whole, this four-fold strategy can be used to safeguard students and avoid violations, rather than simply as a means of punishment.

From a policy perspective, universities and higher education institutions should formulate explicit regulations and guidelines governing the ethical use of AI. These guidelines should be widely disseminated and supported by case-based simulations, clear explanations of the consequences for violations, and alternative solutions that guide responsible student behavior. Additionally, institutions should provide consultation channels and academic support services for students experiencing learning difficulties, thereby reducing the temptation to misuse AI.

While the current findings are based on data from a single regional sample, future cross-cultural and multigroup SEM analyses could validate the extended TPB model across diverse educational systems and policy frameworks, enhancing the model's generalizability and theoretical robustness.

Declarations

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Conflict of Interest

All authors attest that there is no conflict of interest in any matter related to the work.

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Authors' Contributions

MT led this research, directed its course, and drafted and reviewed the manuscript. RPP co-led and conceptualized this research, collected and analyzed the data, drafted the manuscript, and assisted the first author as research manager. ND directed the course of research alongside MT and drafted, reviewed, and revised the manuscript. SB helped RPP contextualize this research and provided recommendations for it based on the comprehensiveness of the context.

Declaration of Generative AI in Scientific Writing

The author acknowledges the use of Generative AI tools, including ChatGPT, in the preparation of the manuscript, particularly in some introductory sections, and limits its use to highlighting the main points that must be included in the introduction. All AI-assisted results were critically reviewed, verified, and substantially edited by the author. The author assumes full responsibility for the originality, accuracy, and integrity of the final product.

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