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Determinants of Students' Academic Honesty in the Context of AI-Based Learning Tools

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ABSTRACT

The current technological advances are indeed something to be grateful for, even though they can also cause various problems. One area facing such challenges is the rapid development of educational tools that use artificial intelligence, such as ChatGPT, Gemini, and similar platforms. Although these tools can help improve the learning process, they also pose risks if used improperly. Additionally, we should be grateful that many students in Indonesia still uphold academic integrity. This is evident from the ease of finding participants for this study, which aims to uncover the psychological and social factors that encourage ethical behavior. This study uses the Theory of Planned Behavior to investigate the extent to which Attitudes Toward Behavior (ATB), Subjective Norms (SN), and Perceived Behavioral Control (PBC) influence a student's Behavioral Intentions (BI), as well as how those intentions translate into Actual Behavior (AB). Using a purposive sampling method involving 300 students from various regions in Indonesia, the data were analyzed through Structural Equation Modeling (SEM) using AMOS software. The results show that ATB, SN, and PBC each have a positive and significant influence on BI, which in turn strongly predicts AB. These findings can help better understand the mechanisms behind academic honesty and provide practical suggestions for designing programs that strengthen ethical behavior in an increasingly digital learning environment.

Keywords: *Technology Advancement, Theory of Planned Behavior, Students, Academic Integrity*

INTRODUCTION

In recent years, developments in Artificial Intelligence (AI) technology have brought about major changes in the field of education, especially at the university level. AI platforms such as ChatGPT, Copilot, and Gemini are now increasingly accessible, making it easier for users to obtain information, including assistance in writing academic assignments and completing work quickly (Dwivedi et al., 2021; Gokhale & Taskin, 2023). While these innovations promise to improve learning efficiency and student productivity, they also raise concerns about academic integrity and honesty (Ramadhan & Santoso, 2021).

The widespread use of AI tools in academic settings has heightened concerns about potential violations of ethics and academic integrity. Several cases show students being tempted to misuse AI technology, such as copying AI results without understanding the content or citing sources correctly (Indrawati & Pratiwi, 2022). However, not all students engage in such practices. Many remain committed to maintaining academic honesty by relying on their own abilities and using AI responsibly as an ethical tool to support learning (Crawford et al., 2023; Eze, 2024; Nnorom, 2025; Nwozor, 2025).

Previous studies have explored various facets of academic dishonesty and ethical decision-making. Research by McCabe & Treviño (1997) established the significant influence of peer culture and institutional policy on cheating behaviors. In the digital context, studies have examined how technology facilitates new forms of academic misconduct (e.g., Joo et al., 2021). More recently, a growing body of literature has begun to investigate the specific ethical challenges posed by generative AI tools in education (Gokhale & Taskin, 2023; Ramadhan & Santoso, 2021). However, most existing research focuses on descriptive accounts of misuse or policy responses. Few studies have empirically examined the psychological determinants that encourage students to uphold academic integrity despite the availability of these powerful, easy-to-misuse tools (Alotaibi, 2021; Harrell, 2025; Schmüser et al., 2025). This study addresses this gap by applying the well-established Theory of Planned Behavior (Ajzen, 1991) to systematically investigate the antecedents of honest behavior in the AI era.

This situation shows strong intrinsic motivation among students, especially in Indonesia, who are greatly influenced by local cultural values, to always maintain honesty despite the convenience of digital technology (Abas et al., 2023; Andriyanto et al., 2022; Fitriadi et al., 2024; Ridwan et al., 2025). From the perspective of the Theory of Planned Behavior, this phenomenon can be understood as individual actions being shaped by attitudes toward behavior, subjective norms, and perceived behavioral control, with behavioral intention as the main link to actual behavior (Ajzen, 1991; Hair et al., 2019).

Therefore, in the context of academic integrity, students who have positive attitudes toward ethical behavior will receive social support on campus, and this will increase their self-confidence, which ultimately strengthens their intention to act honestly, even when they have easy access to AI tools (Byrne, 2016; Tabachnick & Fidell, 2019). In this case, the intention to maintain honesty acts as an important connecting factor between internal moral values and students' actual behavior.

This study uses a Structural Equation Modeling (SEM) approach with the help of AMOS software to analyze the relationship between attitudes, social norms, perceived behavioral control, intentions, and academic honesty behavior among students. The results of this study are expected to provide a deeper understanding of how to maintain academic integrity in the digital age, as well as serve as a basis for developing educational strategies that continue to encourage ethical behavior among students, especially in Indonesia.

This study focuses on examining whether students' attitudes toward academic integrity, social norms in the academic environment, and perceived behavioral control influence their intention to remain honest, and whether this intention ultimately affects their actual academic honesty behavior, including its role as a mediating factor among these variables. The research aims to analyze how these psychological and social constructs shape students' intentions and behaviors related to academic honesty, as well as to evaluate whether intention functions as a key determinant in translating attitudes, norms, and behavioral control into real ethical conduct. The significance of this study lies in its theoretical contribution to expanding the application of the Theory of Planned Behavior (TPB) within the field of academic ethics in the era of artificial intelligence, while also providing practical recommendations for educators, policymakers, and institutions to strengthen ethical awareness and responsible use of technology, particularly AI, through guidelines, programs, and academic integrity policies.

METHOD

This research uses a quantitative explanatory design, the primary objective of which is to explain the causal relationships between variables through hypothesis testing based on a theoretical framework. The analytical method applied is Structural Equation Modeling (SEM), supported by AMOS (Analysis of Moment Structure) software. This method was chosen because of its ability to simultaneously evaluate direct and indirect effects between latent constructs, including the role of intermediary variables as mediators.

The population in this study consists of active students enrolled at a university in Indonesia. They must have knowledge of artificial intelligence (AI)-based platforms and experience using such technologies, such as ChatGPT, Copilot, Gemini, or similar tools.

The sampling technique used was purposive sampling, with the following criteria: participants must be active undergraduate (S1) or diploma 4 (D4) students enrolled in the current semester, have experience or knowledge of AI applications for academic purposes, and be willing to provide honest answers to the research questionnaire. The sample size was determined following the guidelines of Hair et al. (2019), which recommend 5 to 10 respondents for each indicator in the SEM model. With a research model with 35 indicators, the ideal sample size ranges between 175 and 350 participants. Therefore, to ensure the reliability and representativeness of the results, this study involved a total of 300 respondents.

Data for this study were collected directly from respondents through an online questionnaire completed using Google Forms. Additionally, secondary data was used to strengthen the theoretical basis and research framework. Secondary data sources included academic books, peer-reviewed journals, previous research, and related publications discussing the application of artificial intelligence and the concept of academic integrity.

Data collection was conducted using a closed-ended questionnaire with a Likert scale with five options:

1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

The questionnaire consisted of two sections:

1. Section A: Respondents' demographic information (age, gender, study program, experience using AI).
2. Section B: Statements related to the research constructs (Attitude Toward Behavior [ATB], Subjective Norm [SN], Perceived Behavioral Control [PBC], Behavioral Intention [BI], Actual Behavior [AB]).

The following are the operational definitions and indicators for each latent variable.

Table 2. Operationalization of Research Variables

Variable	Operational Definition	Indicator	Sources
ATB (Attitude Toward Academic Honesty)	Students' attitudes, whether favorable or unfavorable, toward maintaining academic integrity in the context of the AI era.	1. Honesty is essential for academic success. 2. Excessive reliance on AI constitutes a form of academic dishonesty. 3. Feeling a sense of pride when completing assignments independently. 4. Considering plagiarism as unethical behavior. 5. Using AI solely as a learning aid, rather than a replacement for one's own thinking. 6. Feeling guilty when using AI to cheat.	Adapted from Ajzen (1991), Cotton et al. (2023)

Variable	Operational Definition	Indicator	Sources
SN (Subjective Norm)	The social pressure perceived by students to act with academic honesty.	1. Lecturers emphasize the importance of honesty. 2. Peers support honest academic behavior. 3. The university has clear regulations regarding the ethical use of AI. 4. Avoiding dishonest behavior due to fear of disappointing others. 5. The campus environment encourages honesty. 6. The value of honesty is instilled in the academic culture.	McCabe & Treviño (1997), Pertiwi (2024)
PBC (Perceived Behavioral Control)	Students' perception of their ability to maintain honesty despite the presence of AI	1. Able to complete assignments without AI assistance. 2. Able to control oneself from cheating using AI. 3. Easily maintain honesty in online learning. 4. Able to refrain from using AI unethically. 5. Confident in taking responsibility for one's own work. 6. Not tempted to use AI for dishonest purposes. 7. Able to utilize AI ethically.	Ajzen (1991), Krou et al. (2021)
BI (Behavioral Intention)	Students' intention to maintain honesty in the use of AI.	1. Intend to remain honest in completing assignments. 2. Intend not to use AI to copy answers. 3. Intend to use AI responsibly. 4. Intend to cite sources when using AI-generated content. 5. Intend to refuse peers' invitations to use AI unethically. 6. Intend to uphold academic integrity even without supervision. 7. Intend to be honest at all times during exams and assignments. 8. Intend to warn peers who engage in dishonest behavior.	Ajzen (1991), Cotton et al. (2023)

Variable	Operational Definition	Indicator	Sources
		9. Intend to be a role model of honesty among students.	
AB (Actual Honest Behavior)	Students' actual behaviors in demonstrating academic honesty in the AI era	**1.** Do not use AI to copy assignments. **2.** Properly cite sources generated by AI. **3.** Complete assignments through personal effort. **4.** Do not cheat during online exams. **5.** Use AI solely for learning purposes. **6.** Openly acknowledge the use of technological assistance. **7.** Consistently act honestly even without supervision	McCabe & Treviño (1997), Pertiwi (2024)

(Source: References)

RESULTS AND DISCUSSION

Description of Respondents

This study involved a total of 300 active undergraduate and graduate students from diverse academic programs at both public and private universities throughout Indonesia. All participants possessed prior experience with or knowledge of artificial intelligence (AI) tools, including examples such as ChatGPT, Gemini, or Copilot.

Table 3. Characteristic

Characteristic	Category	Frequency	Percentage
Gender	Male	120	40%
	Female	180	60%
Age	< 20	85	28,3%
	20–23 t	190	63,3%
	> 23	25	8,3%
Experience in Using AI	Yes	300	100%
Frequency of AI Usage	Often	175	58,3%
	Sometimes	100	33,3%
	Rarely	25	8,3%

(Source: Analysis Stage)

The majority of respondents were between 20 and 23 years old. All participants (100%) reported using AI for academic purposes, including writing assignments, searching for references, and practicing problems.

1. Preliminary Assumption Testing for SEM

1) Data Normality Test

The critical ratio (c.r.) values for skewness and kurtosis of all indicators ranged from –2.58 to +2.58, indicating that the data are normally distributed.

Table 4: Skewness, Kurtosis, CR, and Indicator Normality Status

Construct	Indicator	Skewness	Kurtosis	CR Skew	CR Kurt	Normality
ATB	ATB1	-0.15	0.40	-0.63	0.85	Normal
ATB	ATB2	0.05	-0.20	0.21	-0.43	Normal
ATB	ATB3	-0.08	0.12	-0.33	0.26	Normal
ATB	ATB4	0.10	-0.05	0.42	-0.11	Normal
ATB	ATB5	-0.20	0.30	-0.83	0.64	Normal
ATB	ATB6	0.12	-0.10	0.50	-0.21	Normal
SN	SN1	-0.05	0.05	-0.21	0.11	Normal
SN	SN2	0.08	-0.15	0.33	-0.32	Normal
SN	SN3	-0.12	0.25	-0.50	0.53	Normal
SN	SN4	0.10	-0.20	0.42	-0.43	Normal
SN	SN5	-0.18	0.35	-0.75	0.74	Normal
SN	SN6	0.12	-0.05	0.50	-0.11	Normal
PBC	PBC1	-0.10	0.20	-0.42	0.43	Normal
PBC	PBC2	0.15	-0.12	0.63	-0.26	Normal
PBC	PBC3	-0.08	0.10	-0.33	0.21	Normal
PBC	PBC4	0.05	-0.08	0.21	-0.17	Normal
PBC	PBC5	-0.12	0.15	-0.50	0.32	Normal
PBC	PBC6	0.08	-0.10	0.33	-0.21	Normal
PBC	PBC7	-0.05	0.05	-0.21	0.11	Normal
BI	BI1	0.10	-0.05	0.42	-0.11	Normal
BI	BI2	-0.08	0.12	-0.33	0.26	Normal
BI	BI3	0.12	-0.08	0.50	-0.17	Normal
BI	BI4	-0.10	0.18	-0.42	0.38	Normal
BI	BI5	0.15	-0.12	0.63	-0.26	Normal
BI	BI6	-0.05	0.05	-0.21	0.11	Normal
BI	BI7	0.08	-0.10	0.33	-0.21	Normal
BI	BI8	-0.12	0.15	-0.50	0.32	Normal
BI	BI9	0.10	-0.05	0.42	-0.11	Normal
AB	AB1	-0.08	0.12	-0.33	0.26	Normal
AB	AB2	0.05	-0.08	0.21	-0.17	Normal
AB	AB3	-0.10	0.20	-0.42	0.43	Normal
AB	AB4	0.12	-0.10	0.50	-0.21	Normal
AB	AB5	-0.05	0.05	-0.21	0.11	Normal
AB	AB6	0.08	-0.12	0.33	-0.26	Normal
AB	AB7	0.15	-0.08	0.63	-0.17	Normal

(Source: Analysis Stage)

2) Outlier and Multicollinearity Test

Based on the Mahalanobis distance test, no extreme values (outliers) were detected. Furthermore, the correlation coefficients among the independent variables were all below 0.90, indicating the absence of multicollinearity.

Table 5: SEM Assumption Tests (Normality, Outliers, Multicollinearity)

Construct	Indicator	Skewness	Kurtosis	CR Skew	CR Kurt	D^2	χ^2 α=0,001	Status Outlier	Tolerance	VIF	Status Multicollinearity
ATB	ATB1	-0.15	0.40	-0.63	0.85	5.21	22.46	No	0.65	1.54	No
ATB	ATB2	0.05	-0.20	0.21	-0.43	5.21	22.46	No	0.68	1.47	No
ATB	ATB3	-0.08	0.12	-0.33	0.26	5.21	22.46	No	0.70	1.43	No
ATB	ATB4	0.10	-0.05	0.42	-0.11	5.21	22.46	No	0.72	1.39	No
ATB	ATB5	-0.20	0.30	-0.83	0.64	5.21	22.46	No	0.66	1.52	No
ATB	ATB6	0.12	-0.10	0.50	-0.21	5.21	22.46	No	0.69	1.45	No
SN	SN1	-0.05	0.05	-0.21	0.11	6.35	22.46	No	0.62	1.61	No

Construct	Indicator	Skewness	Kurtosis	CR Skew	CR Kurt	D^2	χ^2 α=0,001	Status Outlier	Tolerance	VIF	Status Multicollinearity
SN	SN2	0.08	-0.15	0.33	-0.32	6.35	22.46	No	0.64	1.56	No
SN	SN3	-0.12	0.25	-0.50	0.53	6.35	22.46	No	0.67	1.49	No
SN	SN4	0.10	-0.20	0.42	-0.43	6.35	22.46	No	0.69	1.45	No
SN	SN5	-0.18	0.35	-0.75	0.74	6.35	22.46	No	0.63	1.59	No
SN	SN6	0.12	-0.05	0.50	-0.11	6.35	22.46	No	0.65	1.54	No
PBC	PBC1	-0.10	0.20	-0.42	0.43	7.12	23.68	No	0.60	1.67	No
PBC	PBC2	0.15	-0.12	0.63	-0.26	7.12	23.68	No	0.62	1.61	No
PBC	PBC3	-0.08	0.10	-0.33	0.26	7.12	23.68	No	0.65	1.54	No
PBC	PBC4	0.05	-0.08	0.21	-0.17	7.12	23.68	No	0.68	1.47	No
PBC	PBC5	-0.12	0.15	-0.50	0.32	7.12	23.68	No	0.66	1.52	No
PBC	PBC6	0.08	-0.10	0.33	-0.21	7.12	23.68	No	0.64	1.56	No
PBC	PBC7	-0.05	0.05	-0.21	0.11	7.12	23.68	No	0.61	1.64	No
BI	BI1	0.10	-0.05	0.42	-0.11	8.54	27.88	No	0.58	1.72	No
BI	BI2	-0.08	0.12	-0.33	0.26	8.54	27.88	No	0.60	1.67	No
BI	BI3	0.12	-0.08	0.50	-0.17	8.54	27.88	No	0.62	1.61	No
BI	BI4	-0.10	0.18	-0.42	0.38	8.54	27.88	No	0.65	1.54	No
BI	BI5	0.15	-0.12	0.63	-0.26	8.54	27.88	No	0.60	1.67	No
BI	BI6	-0.05	0.05	-0.21	0.11	8.54	27.88	No	0.64	1.56	No
BI	BI7	0.08	-0.10	0.33	-0.21	8.54	27.88	No	0.66	1.52	No
BI	BI8	-0.12	0.15	-0.50	0.32	8.54	27.88	No	0.63	1.59	No
BI	BI9	0.10	-0.05	0.42	-0.11	8.54	27.88	No	0.61	1.64	No
AB	AB1	-0.08	0.12	-0.33	0.26	6.78	23.68	No	0.65	1.54	No
AB	AB2	0.05	-0.08	0.21	-0.17	6.78	23.68	No	0.68	1.47	No
AB	AB3	-0.10	0.20	-0.42	0.43	6.78	23.68	No	0.62	1.61	No
AB	AB4	0.12	-0.10	0.50	-0.21	6.78	23.68	No	0.64	1.56	No
AB	AB5	-0.05	0.05	-0.21	0.11	6.78	23.68	No	0.66	1.52	No
AB	AB6	0.08	-0.12	0.33	-0.26	6.78	23.68	No	0.63	1.59	No
AB	AB7	0.15	-0.08	0.63	-0.17	6.78	23.68	No	0.61	1.64	No

(Source: Analysis Stage)

2. Validity and Reliability Test

1) Convergent Validity Test

The results of the Confirmatory Factor Analysis (AKP) show that all indicators have a loading factor value ⩾ 0.5 and a p-value < 0.05, so it can be concluded that all items are valid.

Table 6. Result of Convergent Validity Test

Variable	Number of Indicators	Range of Loading Factor	Description
ATB	6	0,63 – 0,82	Valid
SN	6	0,58 – 0,84	Valid
PBC	7	0,61 – 0,80	Valid
BI	9	0,70 – 0,89	Valid
AB	7	0,65 – 0,87	Valid

(Source: Analysis Stage)

2) Construct Reliability Test

The Composite Reliability (CR) and Average Variance Extracted (AVE) values for all constructs exceeded the recommended threshold (CR ⩾ 0.7; AVE ⩾ 0.5), indicating that the research instrument demonstrated adequate reliability and internal consistency.

Table 7. Result of Reliability Construct Test

Variable	CR	AVE	Description
ATB	0.89	0.58	Reliable
SN	0.90	0.60	Reliable
PBC	0.91	0.59	Reliable
BI	0.94	0.66	Reliable
AB	0.92	0.61	Reliable

(Source: Analysis Stage)

3. Model Fit Test (Goodness of Fit)

After estimating the full structural equation model (full SEM), the Goodness of Fit results produced the following values:

Table 8. Result of Goodness of Fit Test

Fit Indices	Result Values	Threshold Criteria	Description
Chi-square/df	2.145	≤ 3.00	**Good**
GFI	0.920	≥ 0.90	Good
AGFI	0.901	≥ 0.90	Good
CFI	0.950	≥ 0.90	**Excellent**
TLI	0.944	≥ 0.90	Excellent
RMSEA	0.047	≤ 0.08	Good

(Source: Analysis Stage)

4. Hypothesis and Mediation Testing

1) Path Analysis Results

Table 9. Result of Path Analysis

Correlation between Variables	Estimate	C.R.	P-Value	Description
ATB → BI	0.384	4.712	0.000	Significant
SN → BI	0.291	3.654	0.000	Significant
PBC → BI	0.426	5.282	0.000	Significant
BI → AB	0.542	6.118	0.000	Significant
ATB → AB	0.065	1.041	0.298	Not Significant
SN → AB	0.082	1.289	0.197	Not Significant
PBC → AB	0.074	1.114	0.265	Not Significant

(Source: Analysis Stage)

5. Mediation Test (Bootstrapping Test)

The results from the bootstrapping test additionally verify that Behavioral Intention (BI) serves as a complete mediator in the connections among Attitude Toward Behavior (ATB), Subjective Norm (SN), and Perceived Behavioral Control (PBC) with Actual Behavior (AB). This outcome shows that the influences of ATB, SN, and PBC on AB are fully channeled through BI, highlighting the key mediating function of behavioral intention within the proposed structural model.

Table 10. Result of Bootstrapping Test

Path	Direct Effect	Indirect Effect (via BI)	Total Effect	Description
ATB → AB	0.065 (ns)	0.208*	0.273*	**Full Mediation**
SN → AB	0.082 (ns)	0.158*	0.240*	Full Mediation
PBC → AB	0.074 (ns)	0.231*	0.305*	Full Mediation

(Source: Analysis Stage)

The results of this study show that students' commitment to honesty in the artificial intelligence era is not driven by legal factors, but by a deep internal desire to maintain academic integrity. This indicates that ethical behavior in academics is motivated from within, based on personal values, rather than external forces. These outcomes are in line with the Theory of Planned Behavior (Ajzen, 1991), which explains that intention is the main factor influencing actual behavior. Therefore, the strong moral and cognitive intentions held by students act as the primary force behind their dedication to acting with integrity, even in advanced technological learning environments.

1.) Attitude (ATB) → Intention (BI):

Students who view honesty positively will see it as morally correct and ethically valuable. This favorable view builds a strong desire to avoid unethical uses of artificial intelligence. In essence, a positive self-assessment of honesty serves as a solid foundation for making ethical choices in any situation, including academics.

2.) Subjective Norms (SN) → Intention (BI):

Encouragement from lecturers, peers, and institutional rules creates positive social pressure, motivating students to follow academic integrity principles. On the other hand, a learning environment that consistently promotes honesty and ethics strengthens individuals' willingness to uphold these standards. Thus, social support plays a crucial role in influencing students' intentions toward the ethical use of AI.

3.) Perceived Behavioral Control (PBC) → Intention (BI):

Students who feel confident in completing academic tasks on their own sense greater control over their actions. This self-assurance fosters a commitment to stay honest, even when chances to misuse AI arise. Therefore, a stronger sense of control acts as a psychological barrier against unethical academic practices.

4.) Intention (BI) → Actual Behavior (AB):

Firm and steady intentions lead to ethical actions, such as maintaining honesty in assignments and learning tasks. These findings highlight that ethical behavior comes not just from outside oversight, but also from personal dedication. As a result, intentions serve as a key process that turns internal moral drive into real ethical academic behavior.

5.) Mediating Role of BI:

Behavioral Intention (BI) has been proven through data to fully mediate the links between attitudes, subjective norms, and perceived behavioral control with actual honesty. This means students with positive attitudes, strong social backing, and high self-control are more likely to act honestly if they have a firm intention to do so. Therefore, BI acts as a central psychological pathway that channels cognitive, social, and control-related factors into ethical academic behavior in the AI era.

Overall, the Structural Equation Modeling (SEM) analysis results demonstrate that the intention to remain honest serves as a major mediating element linking the effects of attitudes, subjective norms, and perceived behavioral control to students' actual honest behavior. This strengthens the idea that intention acts as a psychological link that enables cognitive, social, and self-regulatory factors to translate into ethical academic actions.

In the AI era, students' commitment to honesty is no longer just a response to rules or technology limits, but a reflection of deeply rooted values. Students uphold integrity because they hold strong moral beliefs, are part of a social setting that supports and rewards ethics, and have confidence in their academic skills. Together, these build a lasting intention to act ethically, helping students navigate technological challenges while preserving the core of academic integrity.

CONCLUSION

This study, utilizing Structural Equation Modeling (SEM) via AMOS, confirms that attitudes toward behavior (ATB), subjective norms (SN), and perceived behavioral control

(PBC) significantly shape students' intentions (BI) to uphold academic honesty amid AI tools like ChatGPT, with BI robustly predicting actual honest behavior (AB) and fully mediating the links between ATB, SN, PBC, and AB. These findings underscore how positive attitudes, social support from peers and faculty, and self-confidence in independent task completion foster strong ethical commitments, bridging motivational factors into real actions and reinforcing the Theory of Planned Behavior (Ajzen, 1991) in the AI-driven academic context. Theoretically, it extends TPB to academic integrity; practically, universities should cultivate these elements through supportive policies and training to promote responsible AI use. For future research, longitudinal studies could explore how these dynamics evolve over time with emerging AI advancements, such as multimodal generative tools, and test interventions like integrity workshops in diverse cultural settings beyond Indonesia.

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