

Academic Honesty in the Age of Artificial Intelligence: A Theory of Planned Behavior Study among Psychology Students in Indonesia

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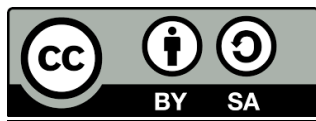
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ABSTRACT

The rapid adoption of artificial intelligence in higher education provides various learning benefits while also creating new challenges for academic integrity, particularly when AI tools replace students' independent reasoning and intellectual efforts. This study aimed to examine academic honesty among Indonesian psychology students by testing the explanatory power of the Theory of Planned Behavior within AI-mediated learning environments. A quantitative cross-sectional survey was conducted among 410 psychology students selected through purposive sampling from public and private universities across Indonesia. Data were collected using a 35-item questionnaire and analyzed using Confirmatory Factor Analysis and Structural Equation Modeling with AMOS. The measurement and structural models demonstrated satisfactory fit, reliability, and validity. Attitudes toward honest behavior, subjective norms, and perceived behavioral control significantly predicted behavioral intention, jointly explaining 63% of its variance. Perceived behavioral control was the strongest predictor of behavioral intention. Furthermore, behavioral intention and perceived behavioral control significantly influenced actual honest behavior and explained 58% of its variance. The findings indicate that academic honesty in AI-rich learning environments is supported by ethical evaluations, positive social expectations, and students' confidence in managing academic demands responsibly. Therefore, universities should combine clear AI-use policies with ethics education, responsible AI literacy, and initiatives that strengthen self-regulation and academic self-efficacy.



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INTRODUCTION

The accelerated proliferation of generative artificial intelligence (AI) technologies has profoundly reshaped academic practices within higher education institutions worldwide (Dai et al., 2026; Jin et al., 2025; Passaris, 2027; Pushpanadham & Sarpong, 2024; Wong, 2024). Tools such as large language models, automated paraphrasing applications, and AI-assisted research platforms have significantly transformed how students access information, develop arguments, and complete academic assignments. When used responsibly, these technologies can enhance learning efficiency, support idea development, and facilitate academic productivity by reducing routine tasks and enabling deeper engagement with course materials (Kasneci et al., 2023; Dwivedi et al., 2023).

However, alongside these potential benefits, the rapid integration of AI tools into academic contexts has generated increasing concerns regarding academic integrity. Ethical challenges arise particularly when AI applications are used not as complementary learning resources but as substitutes for students' cognitive processes, critical reasoning, and intellectual efforts. Such practices may undermine the fundamental objectives of higher education, which include developing independent thinking, conceptual understanding, and scholarly responsibility (Susnjak, 2023; Cotton et al., 2023).

At the global level, universities increasingly face uncertainty regarding authorship, originality, and ethical boundaries in student work. The sophistication of AI-generated content has made it increasingly difficult for educators to distinguish between original student contributions and machine-generated outputs. Consequently, traditional concepts of plagiarism and academic misconduct are being challenged, requiring a re-evaluation of existing academic integrity frameworks and assessment practices (Fawns, 2023; Rudolph et al., 2023).

These challenges are particularly relevant in academic disciplines that emphasize reflective thinking, ethical judgment, and professional accountability, such as psychology. Psychology education is fundamentally based on ethical principles, including honesty, responsibility, and scientific integrity. Students in this discipline are expected not only to develop theoretical and methodological competencies but also to internalize ethical standards that guide academic behavior and future professional practice. Therefore, the ethical implications of AI use in psychology education extend beyond immediate academic outcomes, as they are closely associated with the development of professional identity and moral responsibility (American Psychological Association, 2017; Johnston et al., 2024).

Psychology education differs from many other academic disciplines because of its strong and explicitly established ethical foundation. From the early stages of undergraduate education, psychology students are systematically introduced to ethical principles emphasizing honesty, personal responsibility, scientific integrity, and respect for human dignity. These principles are not merely treated as abstract moral values but are incorporated through ethics-related coursework, discussions of ethical dilemmas, adherence to professional codes, and normative expectations communicated by lecturers and academic institutions (American Psychological Association, 2017; McCabe et al., 2012; Bertram Gallant, 2008).

As a result, psychology students are encouraged to perceive academic honesty not merely as a set of external regulations but as an essential component of their developing professional identity. Honest academic behavior is viewed as an indicator of ethical maturity and professional preparedness, aligning with the moral standards required in future psychological practice. Through continuous ethical socialization, integrity becomes a central criterion through which students evaluate their academic decisions, including decisions regarding the appropriate and ethical use of emerging technologies such as artificial intelligence (Rest et al., 1999; Johnston et al., 2024). Within the broader academic integrity literature, scholars have emphasized that establishing integrity as an institutional value is essential for maintaining trust, credibility, and ethical scholarship in higher education (Bretag, 2016).

In the Indonesian context, academic honesty is also influenced by cultural values emphasizing moral responsibility, social harmony, and personal integrity. These values are embedded within social interactions and reinforced through communal expectations that encourage individuals to act in ways that maintain trust and collective well-being. When combined with formal ethical education in psychology programs, these cultural norms may contribute to the development of a strong internal ethical framework among students.

The interaction between cultural values and professional ethical education has the potential to strengthen students' moral decision-making in academic contexts beyond mere compliance with institutional regulations. Consequently, students may demonstrate greater willingness to avoid unethical academic practices, including inappropriate use of artificial intelligence tools, even when technological shortcuts are easily accessible and difficult to identify.

Although previous studies have predominantly focused on identifying factors contributing to students' misuse of artificial intelligence in academic settings, limited attention has been given to understanding why many students intentionally maintain ethical academic behavior. Existing literature has largely emphasized risk factors, detection mechanisms, and policy enforcement related to AI-enabled academic misconduct, often positioning students as potential offenders rather than ethical decision-makers (Cotton et al., 2023; Susnjak, 2023; Perkins, 2023). This imbalance has resulted in limited understanding of the psychological and social mechanisms that support academic honesty, particularly in disciplines with strong ethical orientations such as psychology.

Furthermore, research on academic integrity in the era of artificial intelligence has frequently emphasized technological detection systems, institutional monitoring, and regulatory approaches designed to prevent misconduct. Although these approaches remain important, they often overlook internal motivations and social influences that encourage students to maintain integrity despite opportunities for unethical AI use. Understanding the factors that sustain honest academic behavior is therefore essential for developing more sustainable academic integrity strategies within higher education.

Moreover, empirical studies applying established behavioral theories to explain students' ethical resilience in AI-enhanced learning environments remain limited. Although frameworks such as the Theory of Planned Behavior (TPB) have been widely validated for predicting ethical and academic behaviors, their application in explaining academic honesty within AI-assisted learning contexts remains relatively underexplored (Ajzen, 1991; Fawns, 2023).

Based on this research gap, this study aimed to provide a comprehensive explanation of the factors that enabled psychology students in Indonesia to maintain academic honesty amid the rapid development of artificial intelligence technologies. Rather than focusing solely on AI misuse, this study emphasized students' ethical decision-making processes and their ability to maintain integrity within AI-mediated learning environments.

Specifically, this research examined the applicability and explanatory power of the Theory of Planned Behavior (TPB) in explaining academic honesty when advanced AI tools were readily available. By analyzing attitudes toward honest behavior, subjective norms, and perceived behavioral control, this study evaluated how psychological and social factors influenced students' intentions and actual academic behavior.

Furthermore, this study contributed empirical evidence through the application of Structural Equation Modeling using AMOS (SEM-AMOS), based on data collected from a broad national sample of psychology students across Indonesia. Through this approach, the research strengthened the empirical application of TPB in technology-enhanced educational settings and provided practical insights for educators and policymakers in promoting ethical AI use and academic integrity in higher education.

METHOD

This study adopted a quantitative, cross-sectional survey design to empirically examine the Theory of Planned Behavior (TPB) model in the context of academic honesty among psychology students. A quantitative approach was applied because the study aimed to test relationships among latent psychological constructs and evaluate their explanatory power using statistical modeling techniques. The cross-sectional design enabled data collection from a large sample at a single point in time to capture students' attitudes, perceived social influences, perceived behavioral control, intentions, and actual academic behavior within an AI-mediated learning environment.

Structural Equation Modeling (SEM) was used as the primary analytical method because it allowed simultaneous evaluation of the measurement and structural models while accounting for measurement error. This approach was suitable for testing complex relationships among latent variables and assessing the applicability of the TPB model in explaining academic honesty in higher education. By integrating Confirmatory Factor Analysis and path analysis, SEM provided a systematic evaluation of the proposed research model.

Participants and Sampling

The target population of this study consisted of undergraduate students enrolled in psychology programs at public and private universities across Indonesia. Psychology students were selected as the focus of this research due to the ethical orientation of their academic training and the relevance of academic honesty to their future professional roles. To ensure that respondents were able to provide informed and meaningful responses, participation was limited to students who were actively enrolled and familiar with the use of artificial intelligence tools in academic contexts, such as AI-based writing assistants, paraphrasing tools, or research-support applications.

A purposive sampling technique was employed to recruit participants who met these criteria. This non-probability sampling approach was considered appropriate given the study's emphasis on theory testing rather than population estimation, as well as the need to ensure that all respondents had sufficient exposure to AI-assisted learning environments. Data were collected from 410 psychology students representing diverse universities and geographic regions within Indonesia, thereby enhancing the heterogeneity of the sample and the generalizability of the findings within the context of psychology education.

The sample size exceeded commonly recommended thresholds for Structural Equation Modeling, which suggest a minimum of 200 respondents or a ratio of at least 5–10 observations per estimated parameter to ensure stable and reliable model estimation. With 35 observed indicators and multiple latent constructs, the obtained sample was deemed adequate to support robust parameter estimation, model fit evaluation, and hypothesis

testing. Moreover, the relatively large sample size strengthened the statistical power of the analysis and reduced the likelihood of estimation bias.

Demographically, the participants reflected the typical characteristics of undergraduate psychology students in Indonesia in terms of age and academic standing. While demographic variables were not treated as focal predictors in the structural model, the diversity of the sample provided a meaningful empirical basis for examining patterns of academic honesty across a broad range of educational settings. All participants took part voluntarily, and no incentives were provided to minimize response bias and encourage genuine self-reporting.

Instrumentation

The research instrument consisted of a structured questionnaire comprising a total of 35 items, all measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire was designed to capture respondents' perceptions and self-reported behaviors related to academic honesty within an AI-mediated learning environment.

Specifically, the instrument measured five latent constructs derived from the Theory of Planned Behavior. Attitude Toward Behavior (ATB) was assessed using six items reflecting students' moral evaluations and beliefs regarding honest academic conduct. Subjective Norms (SN) were measured through six items capturing perceived social expectations from lecturers, peers, and academic institutions concerning ethical behavior. Perceived Behavioral Control (PBC) was operationalized with seven items assessing students' confidence in their ability to maintain academic honesty despite academic pressure and access to AI-based tools. Behavioral Intention (INT) was measured using nine items reflecting students' deliberate commitment to engage in honest academic practices. Finally, Actual Honest Behavior (AB) was assessed through seven items capturing self-reported ethical conduct in academic activities.

All measurement items were adapted from previously validated TPB-based instruments and established academic integrity scales, ensuring strong content validity and theoretical alignment. To enhance contextual relevance, the items were carefully modified to reflect scenarios involving the use of artificial intelligence tools in academic settings, such as AI-assisted writing, paraphrasing, and research support. This contextualization process ensured that the instrument accurately captured students' ethical decision-making in contemporary AI-rich learning environments while preserving the psychometric integrity of the original scales.

Data Analysis Procedure

Data analysis was conducted through a structured, two-stage analytical procedure to ensure the rigor and validity of the proposed research model. This sequential approach allowed for a clear distinction between the evaluation of the measurement properties of the constructs and the testing of the hypothesized structural relationships among them.

In the first stage, Confirmatory Factor Analysis (CFA) was performed to assess the adequacy of the measurement model. CFA was employed to examine the reliability and validity of the latent constructs by evaluating factor loadings, internal consistency, and convergent and discriminant validity. This step was essential to confirm that the observed indicators accurately represented their respective theoretical constructs before proceeding to

structural analysis. Model fit was assessed using multiple goodness-of-fit indices to ensure that the measurement model demonstrated an acceptable fit to the empirical data.

In the second stage, structural model testing was conducted to examine the hypothesized causal relationships among the latent variables specified by the Theory of Planned Behavior. This phase focused on estimating standardized path coefficients, testing the significance of hypothesized effects, and evaluating the overall explanatory power of the model. In particular, the analysis assessed the extent to which attitudes, subjective norms, and perceived behavioral control predicted behavioral intention, as well as how intention and perceived behavioral control influenced actual honest behavior.

All analyses were carried out using AMOS, which was selected due to its suitability for theory-driven Structural Equation Modeling and its capacity to simultaneously estimate complex relationships among multiple latent constructs while accounting for measurement error. AMOS was used to compute model fit indices, standardized regression weights, critical ratios, and explained variance (R^2) for endogenous variables, thereby providing a comprehensive evaluation of both the measurement and structural components of the proposed model.

RESULTS AND DISCUSSION

Measurement Model

The measurement model was first evaluated using Confirmatory Factor Analysis (CFA) to assess the reliability and validity of the latent constructs included in the proposed TPB framework. The CFA results indicated that the measurement model demonstrated a satisfactory fit to the data. Specifically, the goodness-of-fit indices met commonly accepted thresholds ($\chi^2/df = 1.87$; CFI = 0.934; TLI = 0.926; RMSEA = 0.046), suggesting that the hypothesized factor structure adequately represented the observed data.

All observed indicators loaded significantly on their respective latent constructs, with standardized factor loadings exceeding the recommended minimum value of 0.60. This indicates that each item contributed meaningfully to the measurement of its underlying construct. No items were removed, as all indicators met both statistical and theoretical criteria for retention.

Table 1. Confirmatory Factor Analysis Results

Construct	Item	Standardized Loading	CR
ATB	ATB1	0.72	
	ATB2	0.78	
	ATB3	0.75	
	ATB4	0.81	
	ATB5	0.77	
	ATB6	0.74	
SN	SN1	0.70	
	SN2	0.76	
	SN3	0.73	
	SN4	0.79	
	SN5	0.75	
	SN6	0.72	
PBC	PBC1	0.68	

Construct	Item	Standardized Loading	CR
INT	PBC2	0.74	
	PBC3	0.77	
	PBC4	0.81	
	PBC5	0.76	
	PBC6	0.79	
	PBC7	0.73	
	INT1	0.71	
	INT2	0.78	
	INT3	0.82	
	INT4	0.76	
	INT5	0.80	
	INT6	0.83	
	INT7	0.79	
	INT8	0.75	
	INT9	0.77	
AB	AB1	0.72	
	AB2	0.76	
	AB3	0.81	
	AB4	0.78	
	AB5	0.74	
	AB6	0.79	
	AB7	0.77	

Sources: Author' calculation

Reliability and Convergent Validity

Composite Reliability (CR) and Average Variance Extracted (AVE) were calculated to evaluate internal consistency and convergent validity. As presented in Table 2, all CR values exceeded the recommended threshold of 0.70, indicating strong construct reliability. Similarly, AVE values for all constructs were above the minimum criterion of 0.50, confirming adequate convergent validity.

Table 2. Reliability and Convergent Validity

Construct	Cronbach's α	Composite Reliability (CR)	AVE
ATB	0.88	0.89	0.57
SN	0.86	0.87	0.54
PBC	0.90	0.91	0.59
INT	0.92	0.93	0.61
AB	0.89	0.90	0.58

Sources: Author' calculation

These results indicate that the constructs exhibit high internal consistency and that the indicators share a substantial proportion of variance with their respective latent variables.

Discriminant Validity

Discriminant validity was assessed using the Fornell–Larcker criterion. As shown in Table 3, the square roots of AVE (displayed along the diagonal) were greater than the inter-

construct correlations, providing evidence that each construct is empirically distinct from the others.

Table 3. Discriminant Validity (Fornell–Larcker Criterion)

Construct	ATB	SN	PBC	INT	AB
ATB	0.75				
SN	0.48	0.73			
PBC	0.52	0.46	0.77		
INT	0.61	0.58	0.64	0.78	
AB	0.54	0.49	0.59	0.66	0.76

Sources: Author' calculation

Summary of Measurement Model

Overall, the CFA results confirm that the measurement model is both reliable and valid. All constructs demonstrated strong internal consistency, satisfactory convergent validity, and adequate discriminant validity. These findings indicate that the measurement instruments were psychometrically sound and suitable for subsequent structural model analysis. Accordingly, the study proceeded to test the hypothesized relationships among constructs using Structural Equation Modeling.

Structural Model

The structural model was evaluated to test the hypothesized relationships among the constructs specified by the Theory of Planned Behavior. Overall, the model demonstrated a good fit to the data ($\chi^2/df = 1.94$; CFI = 0.928; TLI = 0.921; RMSEA = 0.048), indicating that the proposed structural relationships adequately represented the empirical data.

All hypothesized paths were found to be statistically significant and in the expected directions, providing full support for the proposed model. As summarized in Table 4, Attitude Toward Behavior (ATB) had a significant positive effect on Behavioral Intention (INT) ($\beta = 0.31$, CR = 5.87, $p < .001$), suggesting that students who hold stronger ethical evaluations toward honest academic behavior are more likely to form firm intentions to behave honestly. This finding underscores the central role of moral attitudes in shaping intentional ethical conduct.

Similarly, Subjective Norms (SN) exerted a significant influence on behavioral intention ($\beta = 0.27$, CR = 5.14, $p < .001$). This result indicates that perceived expectations from lecturers, peers, and academic institutions play a substantial role in motivating psychology students to maintain academic honesty. The strength of this relationship highlights the importance of social and normative pressures in ethically grounded academic disciplines.

Perceived Behavioral Control (PBC) also demonstrated a strong and significant effect on behavioral intention ($\beta = 0.34$, CR = 6.42, $p < .001$), indicating that students who feel confident in their ability to manage academic demands without relying on unethical AI use are more inclined to intend honest behavior. Among the three predictors, PBC emerged as the strongest determinant of intention, emphasizing the importance of self-efficacy and self-regulation in AI-rich learning environments.

Behavioral intention, in turn, significantly predicted Actual Honest Behavior (AB) ($\beta = 0.49$, CR = 8.76, $p < .001$), confirming its role as the most proximal determinant of action

within the TPB framework. This result suggests that students who explicitly intend to behave honestly are substantially more likely to translate these intentions into consistent ethical academic practices.

In addition to its indirect effect through intention, Perceived Behavioral Control also exerted a significant direct influence on actual honest behavior ($\beta = 0.32$, $CR = 6.01$, $p < .001$). This finding indicates that students' perceived capacity to regulate their academic behavior enables them to maintain honesty even in situations where intentions may be challenged by time pressure, workload, or easy access to AI-based shortcuts.

Table 4. Structural Model Path Estimates

Hypothesis	Path	Standardized β	CR	p-value	Result
H1	ATB $\rightarrow$ INT	0.31	5.87	< .001	Supported
H2	SN $\rightarrow$ INT	0.27	5.14	< .001	Supported
H3	PBC $\rightarrow$ INT	0.34	6.42	< .001	Supported
H4	INT $\rightarrow$ AB	0.49	8.76	< .001	Supported
H5	PBC $\rightarrow$ AB	0.32	6.01	< .001	Supported

Sources: Author' calculation

Explained Variance

The model demonstrated strong explanatory power for the endogenous constructs. The three antecedent variables (ATB, SN, and PBC) jointly explained 63% of the variance in Behavioral Intention ($R^2 = 0.63$), indicating a substantial level of predictive accuracy. Furthermore, Behavioral Intention and Perceived Behavioral Control together accounted for 58% of the variance in Actual Honest Behavior ($R^2 = 0.58$), suggesting that both motivational and self-regulatory mechanisms play critical roles in sustaining academic honesty among psychology students.

Summary of Structural Model Findings

Taken together, these findings provide robust empirical support for the applicability of the Theory of Planned Behavior in explaining academic honesty within AI-mediated learning environments. The results highlight that psychology students' honest academic behavior is shaped not only by their ethical intentions but also by their perceived ability to manage academic challenges without resorting to unethical AI use. This pattern reinforces the view that fostering ethical attitudes, supportive social norms, and strong self-regulatory capacity is essential for promoting responsible AI use in higher education.

The findings of this study indicate that psychology students' commitment to academic honesty is driven primarily by deeply internalized ethical attitudes rather than by fear of external sanctions or institutional punishment. This pattern suggests that honest academic behavior among psychology students is rooted in moral conviction and professional values rather than compliance motivated by surveillance or deterrence. Such internalized ethical orientations appear to guide students' academic decisions even in contexts where the likelihood of detection is low and opportunities for unethical AI use are readily available.

This result aligns with longstanding research in academic integrity, which emphasizes that ethical conduct in higher education is more sustainably maintained through internalized values than through purely punitive or surveillance-based mechanisms (McCabe et al., 2012; Pavela, 1997). Earlier studies on academic misconduct similarly indicate that students'

ethical attitudes and moral beliefs are among the strongest predictors of honest academic behavior, often outweighing the deterrent effects of institutional sanctions or monitoring systems (Whitley, 1998; Simkin & McLeod, 2010). When students perceive honesty as a core component of their academic and professional identity, they are more likely to maintain ethical behavior even when technological opportunities for misconduct increase.

The significant role of subjective norms further highlights the importance of social and institutional expectations in shaping ethical behavior. Perceived expectations from lecturers, peers, and academic institutions contribute to the formation of a normative environment in which academic honesty is socially reinforced and collectively valued. Within psychology education, such norms are closely connected to professional ethical standards and codes of conduct, which emphasize honesty as a fundamental requirement for scientific credibility and responsible psychological practice. Consequently, the presence of strong normative guidance may strengthen students' motivation to uphold academic integrity even when AI-assisted shortcuts are easily accessible.

Another key finding concerns the influence of perceived behavioral control on both behavioral intention and actual honest behavior. Students who believe they possess the capability to complete academic tasks independently are less likely to perceive unethical AI use as necessary or justified. This highlights the importance of academic self-efficacy and self-regulatory capacity in maintaining integrity in AI-mediated learning environments. When students feel confident in their ability to manage academic workload and learning challenges, they are better equipped to resist situational temptations such as time pressure, performance anxiety, or technological convenience.

Taken together, these findings suggest that what may be described as **ethical resilience** plays a crucial role in sustaining academic honesty in the era of artificial intelligence. Ethical resilience refers to students' capacity to maintain moral commitments despite the presence of situational pressures, technological opportunities for misconduct, or perceived academic challenges. Rather than relying solely on technological restrictions or punitive control systems, higher education institutions may therefore benefit from strengthening the ethical foundations that support such resilience.

From an academic integrity perspective, this implies that promoting honesty in AI-rich learning environments requires more than surveillance technologies or restrictive AI policies. Educational strategies that cultivate ethical awareness, reinforce professional identity, and support students' self-regulatory competence may be more effective in sustaining long-term integrity. In disciplines such as psychology, where professional ethics are central to academic training, integrating discussions of responsible AI use into ethics education may play an important role in reinforcing students' commitment to honest academic conduct.

CONCLUSION

This study confirmed that the Theory of Planned Behavior effectively explained academic honesty among Indonesian psychology students in AI-mediated learning environments. Attitudes toward honest behavior, subjective norms, and perceived behavioral control significantly strengthened students' behavioral intentions, collectively explaining 63% of the variance in behavioral intention. Behavioral intention and perceived behavioral control

subsequently explained 58% of the variance in actual honest behavior. Perceived behavioral control was the strongest predictor of behavioral intention, while behavioral intention was the strongest direct predictor of honest behavior. These findings demonstrated that maintaining academic honesty amid widespread AI availability depended on students' ethical convictions, supportive social expectations, and confidence in managing academic demands without misusing AI. Therefore, universities should complement AI policies with ethics education, responsible AI literacy, supportive academic norms, and programs that strengthen students' self-regulation and academic self-efficacy.

Future research should employ longitudinal or experimental designs to examine whether students' intentions consistently translate into honest behavior over time and to establish stronger causal relationships among TPB constructs. Because this study relied on purposive sampling and self-reported data from psychology students, subsequent research should involve probability-based samples across disciplines, universities, and cultural contexts while incorporating behavioral observations, lecturer assessments, or digital learning records to minimize social desirability bias. Researchers could also extend the model by examining additional variables, such as moral identity, ethical resilience, AI literacy, academic pressure, institutional policy clarity, and the type or intensity of AI use. Comparative and intervention-based studies are particularly recommended to identify educational strategies that effectively promote responsible AI use and sustainable academic integrity.

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