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Determinants of Honest Academic Behavior Among Indonesian Non-Engineering Students in the Era of AI: A TPB-Based Structural Equation Modeling Study

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Abstract
The rapid integration of artificial intelligence (AI) tools has reshaped learning practices across non-engineering disciplines—including social sciences, business, humanities, education, and law—while raising concerns about academic integrity in writing-intensive fields. This study examines psychological factors promoting honest academic behavior among Indonesian non-engineering students, using the Theory of Planned Behavior as its foundation. In total, 375 Indonesian undergraduates completed an online survey with 35 Likert-scale items measuring attitude toward honest behavior (ATB), subjective norms (SN), perceived behavioral control (PBC), behavioral intention (BI), and actual honest behavior (AB). Data were analyzed via structural equation modeling (SEM) in AMOS. Results show ATB, SN, and PBC significantly predict BI (52% variance explained). BI is the strongest predictor of AB ($\beta = 0.61, p < .001$), with PBC adding a modest direct effect ($\beta = 0.12, p = .028$); together, they explain 48% of AB variance. Bootstrapping confirmed BI's mediating role in all pathways. These findings extend TPB to AI-enhanced non-engineering contexts, highlighting ethical attitudes, social influence, and perceived competence for academic integrity. They offer insights for tailored AI-use policies in higher education.
Keywords: Academic Integrity, Artificial Intelligence in Education, Non-Engineering Students, Theory of Planned Behavior, Structural Equation Modeling, Ethical Behavior, Higher Education.

INTRODUCTION

The rapid advancement of artificial intelligence (AI) technologies—including ChatGPT, Gemini, Perplexity, automated summarization applications, and generative writing assistants—has significantly reshaped academic practices across non-engineering disciplines such as the social sciences, business, humanities, education, psychology, and law. These tools provide notable educational advantages by supporting deeper conceptual understanding, expanding access to information, increasing learning efficiency, and assisting with academic writing processes (Kasneci et al., 2023; Susnjak, 2023). However, the proliferation of AI technologies has simultaneously triggered a global academic integrity crisis. According to recent surveys, approximately 30–40% of students worldwide admit to using AI tools inappropriately for academic work, ranging from unattributed text generation to complete assignment substitution (Bailey, 2023; Nguyen et al., 2023). This phenomenon represents a fundamental shift in the nature of academic misconduct, moving beyond traditional plagiarism to encompass AI-facilitated forms of deception that are increasingly difficult to detect and regulate.

At the same time, the growing accessibility of AI technologies has intensified concerns related to academic integrity (Khatri & Karki, 2023; Nnorom, 2025; Nwozor, 2025; Yusuf et al., 2024). Students may increasingly rely on AI-generated content to produce essays, summaries, analyses, or responses with limited personal engagement, potentially circumventing critical thinking and undermining the authenticity of scholarly work (Cotton et al., 2023; Dawson et al., 2023). In the Indonesian context, empirical evidence suggests that academic dishonesty remains a persistent challenge across higher education institutions. A national study conducted by the Indonesian Ministry of Education and Culture (2022) revealed that 65% of undergraduate students reported witnessing academic misconduct among their peers, while 42% admitted to engaging in at least one form of dishonest academic behavior during their studies. The introduction of accessible AI tools has compounded this issue, with preliminary investigations indicating that over 50% of Indonesian students have used AI assistants for coursework, though the ethical boundaries of such use remain poorly understood (Kalolo, 2021; Simkin & McLeod, 2010).

In Indonesia, the issue of academic honesty becomes more complex due to the country's vast cultural diversity and long-standing traditions of local wisdom. Indonesian cultural norms—such as *gotong royong*, *tepa selira*, *siri' na pacce*, *piil pesenggiri*, and other indigenous values—play a significant role in shaping ethical perspectives, moral conduct, and personal integrity (Haryanto, 2019; Siswanto, 2020). While local wisdom influences ethical orientations, this study incorporates it only as background context, not as a mediating or moderating variable, to maintain theoretical focus.

To examine the psychological factors underlying honest academic behavior in AI-supported learning contexts, this study draws on the Theory of Planned Behavior (TPB) (Ajzen, 1991), a widely recognized model for explaining and predicting human behavior. According to TPB, individuals' actions are influenced by three key determinants: attitude toward the behavior (ATB), subjective norms (SN), and perceived behavioral control (PBC). These factors jointly shape behavioral intention (BI), which in turn guides actual behavior (AB). Previous research has demonstrated the effectiveness of TPB in explaining ethical decision-making, intentions to plagiarize, and academic misconduct across diverse educational contexts (Beccaria et al., 2019; Lin & Chen, 2022).

Despite growing scholarly attention to AI-related misconduct and academic integrity, empirical evidence remains limited regarding the behavioral drivers of academic honesty among non-engineering students in Indonesia. This gap is noteworthy, as students in non-technical disciplines frequently engage in writing-intensive assignments where AI tools are particularly prone to misuse. The phenomenon driving this research is multifaceted: Indonesian non-engineering students face increasing academic pressure, widespread AI tool availability, unclear institutional policies regarding ethical AI use, and cultural norms that may emphasize collective achievement over individual accountability. This convergence of factors creates an urgent need to understand what motivates students to maintain honesty when confronted with easily accessible technological shortcuts.

The urgency of this investigation is underscored by three converging realities. First, the rapid integration of AI into educational ecosystems has outpaced the development of effective ethical frameworks and institutional policies, creating a regulatory vacuum that may inadvertently enable misconduct (Dawson et al., 2023). Second, non-engineering disciplines are particularly vulnerable because their assessment methods—essays, critical analyses, reflective papers—align closely with AI capabilities, making undetected misuse increasingly feasible (Nguyen et al., 2023). Third, without an empirically grounded understanding of what drives honest behavior in this population, universities risk implementing ineffective or counterproductive integrity policies that fail to address the psychological and cultural realities shaping student decision-making.

The novelty of this study lies in its integrated approach that extends TPB application to a previously unexamined intersection: non-engineering Indonesian students in AI-enhanced learning contexts. Unlike prior research that treats academic integrity as a universal construct, this study explicitly accounts for disciplinary differences, cultural context, and technological mediation. Furthermore, by examining both the direct and mediated pathways through which psychological determinants influence behavior, this research provides nuanced insights into the mechanisms underlying ethical decision-making that can inform targeted interventions.

Addressing this gap, the present study applies the TPB framework to a sample of 375 Indonesian non-engineering undergraduates to explore the factors that encourage students to uphold academic honesty in the presence of readily accessible AI technologies. The incorporation of generative AI into higher education has introduced both expanded learning possibilities and heightened risks to academic integrity, with students in non-technical disciplines being especially susceptible due to their text-based assignments. Although prior studies suggest that AI misuse is becoming widespread, empirical research focusing on Indonesian higher education—particularly among non-engineering student populations—remains scarce (Cotton et al., 2023; Dawson et al., 2023). While TPB offers a robust framework for understanding ethical conduct, its application within AI-enabled academic environments and among these students has received limited attention, and the potential influence of Indonesian cultural values on such decisions has not been sufficiently examined. In light of these gaps, a systematic investigation is warranted to identify the key factors influencing honest academic behavior among Indonesian non-engineering students when faced with AI-based tools.

To guide this investigation, the study is driven by research questions focusing on the psychological determinants of honest behavior. It seeks to understand the extent to which students' attitude (ATB), subjective norms (SN), and perceived behavioral control (PBC) influence their behavioral intention (BI) to act honestly, and subsequently, how this intention translates into actual honest academic behavior (AB). A final question examines whether PBC exerts a direct effect on actual behavior beyond its influence through intention. Correspondingly, the research objectives are to investigate the influence of ATB on BI, examine the role of SN, analyze the contribution of PBC to intention formation, assess the impact of BI on AB, and evaluate any direct effect of PBC on honest behavior.

The study is designed as a comprehensive empirical examination, focusing on undergraduate non-engineering students across Indonesian universities, with a sample of 375 respondents. It employs TPB as its primary conceptual model, where ATB, SN, and PBC are antecedents of BI, which predicts AB. Cultural values are included only as descriptive background, not as mediating or moderating variables. Methodologically, it uses a quantitative design with structural equation modeling (SEM) in AMOS, employing a structured questionnaire of 35 Likert-scale items across the five constructs.

This research holds significant theoretical and practical value. Theoretically, it extends TPB by applying it to AI-mediated academic environments in non-engineering disciplines and enhances understanding of ethical behavior in culturally diverse contexts within developing countries. Practically, it assists universities in developing context-sensitive AI-use policies, offers educators insights for strengthening integrity in writing-intensive courses, informs policymakers about the psychological factors shaping ethical AI use, and supports the design of targeted training programs to promote ethical AI use and academic integrity.

Specifically, this research aims to: (1) empirically test the applicability of TPB in predicting honest academic behavior within AI-mediated learning environments among non-engineering students; (2) quantify the relative contributions of attitudes, social norms, and perceived control in shaping behavioral intentions and actual conduct; (3) examine both direct and indirect pathways through which these determinants influence behavior; (4) provide evidence-based insights for developing culturally sensitive and discipline-specific academic integrity policies in Indonesian higher education; and (5) contribute theoretical advancement by extending TPB to emerging technological contexts that fundamentally alter the nature of academic work. The findings of this study offer both theoretical contributions to behavioral ethics literature and practical implications for educators, policymakers, and institutional leaders navigating the complex ethical landscape of AI-enhanced education.

RESEARCH METHOD

This study adopts a quantitative, explanatory research design to investigate the psychological determinants of honest academic behavior among Indonesian non-engineering undergraduate students in the context of the increasing availability of AI-based learning tools. Anchored in the Theory of Planned Behavior (TPB), the research design seeks to explain the causal mechanisms linking attitudes, social influences, and perceived behavioral control to students' intentions and actual academic conduct. To achieve this objective, Structural Equation Modeling (SEM) using AMOS is employed to examine both the measurement properties of the constructs and the structural relationships among the latent variables.

Structural Equation Modeling is selected as the primary analytical technique due to its capacity to simultaneously evaluate the reliability and validity of the measurement model while estimating complex structural relationships among constructs. SEM also offers advantages in handling measurement error and testing mediation effects, making it particularly appropriate for theory-driven models such as TPB that involve multiple interrelated variables (Kline, 2016).

The target population of this study comprises Indonesian undergraduate students who are enrolled in non-engineering academic programs across a range of higher education institutions. These programs include, but are not limited to, the social sciences, business and management, humanities, education, psychology, law, communication studies, and other closely related disciplines. Students within these fields typically engage in coursework that emphasizes writing, critical analysis, and conceptual understanding, making them particularly relevant for examining issues of academic honesty in AI-mediated learning environments..

A total of 375 valid questionnaires were obtained and included in the final analysis. This sample size satisfies established recommendations for Structural Equation Modeling (SEM), which suggest a minimum of 10 to 15 respondents for each observed indicator to ensure stable and reliable parameter estimates (Hair et al., 2019). Given that the measurement model in this study consists of 35 indicators, the minimum required sample size was approximately 350 participants. Therefore, the achieved sample not only meets but exceeds this threshold, providing adequate statistical power for model estimation and hypothesis testing

To achieve broad national representation while maintaining practical feasibility, this study employed a multi-stage sampling strategy. First, stratified sampling was applied based on major geographical regions of Indonesia, including Sumatra, Java, Kalimantan, Sulawesi, Bali–Nusa Tenggara, Maluku, and Papua. This stratification was intended to capture regional diversity and reduce potential geographic bias in the sample.

Subsequently, purposive–convenience sampling was utilized within each regional stratum to recruit participants who met the study criteria, namely undergraduate students enrolled in non-engineering programs. Participants were reached through academic and institutional networks, online student communities, course-related group chats, and faculty-managed mailing lists. This combined approach allowed the study to balance representativeness with accessibility, ensuring sufficient sample coverage across Indonesia's diverse higher education landscape.

The research instrument was organized into three main sections to ensure comprehensive data collection while maintaining clarity and ethical standards.

First, the demographic section gathered background information on participants, including age, gender, academic program, year of study, region of origin, and cultural background. This information was used to describe the sample characteristics and to provide contextual insights into the diversity of the respondents.

Second, the Theory of Planned Behavior (TPB) constructs section consisted of 35 measurement items designed to assess the five latent variables included in the study. All items were measured using a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly* *agree*), allowing respondents to indicate the extent of their agreement with statements related to academic honesty and the ethical use of AI tools.

Third, the instructions and ethical consent section informed participants about the voluntary nature of their participation, assured anonymity and confidentiality of responses, and clearly explained how the collected data would be used solely for academic research purposes. Participants were required to indicate their informed consent before proceeding with the questionnaire.

The questionnaire items were adapted from previously validated instruments grounded in the Theory of Planned Behavior and academic integrity research to ensure conceptual rigor and measurement reliability. Specifically, item formulations were drawn from established studies by Stone et al. (2010), Beccaria et al. (2019), and Lin and Chen (2022), which have been widely used to examine ethical behavior and academic misconduct in higher education contexts.

To enhance contextual relevance, these items were carefully modified to reflect contemporary AI-mediated academic environments. The adaptation process was informed by recent literature on AI and academic integrity, including studies by Cotton et al. (2023), Kasneci et al. (2023), and Nguyen et al. (2023). This approach ensured that the instrument captured students' attitudes, intentions, and behaviors related not only to traditional academic honesty but also to the ethical use of AI-based tools in learning and assessment activities.

Prior to the main data collection, a pilot study was conducted involving 45 undergraduate students enrolled in non-engineering programs. The purpose of the pilot test was to evaluate the clarity, reliability, and overall suitability of the measurement instrument within the targeted academic context.

The results of the pilot analysis indicated satisfactory internal consistency across all constructs, with Cronbach's alpha coefficients equal to or exceeding .78. These values exceed commonly accepted thresholds for reliability, suggesting that the items within each construct were consistently measuring the intended concepts. Based on feedback from the pilot participants, minor revisions were made to the wording of several items to enhance clarity, reduce potential ambiguity, and ensure that the statements were easily understood by students from diverse academic backgrounds.

Data were collected through an online survey administered via Google Forms, which facilitated broad and efficient access to participants across different regions of Indonesia. The data collection process followed several structured steps to ensure ethical compliance and data quality.

First, the survey link was disseminated through multiple academic channels, including university coordinators, student associations, and course-related or institutional group chats, in order to reach eligible non-engineering undergraduate students. Second, an informed consent statement was presented on the initial page of the questionnaire, clearly explaining the purpose of the study, the voluntary nature of participation, and participants' rights.

To protect respondents' privacy, anonymity and confidentiality were strictly maintained, and no personally identifiable information was collected. The data collection period spanned approximately no more than twelve weeks, allowing sufficient time to obtain responses from a geographically diverse sample. Finally, the dataset was screened for potential duplicate submissions using IP address checks and timestamp comparisons to ensure the integrity and validity of the collected data.

Data analysis was performed using SPSS version 26 and AMOS version 26 to ensure rigorous and comprehensive statistical examination. SPSS 26 was utilized for preliminary analyses, including data screening, handling of missing values, descriptive statistics, and assessment of basic assumptions such as normality and reliability. This step provided an initial understanding of the data structure and ensured that the dataset met the requirements for subsequent modeling.

AMOS 26 was then employed to conduct Structural Equation Modeling (SEM), allowing for simultaneous evaluation of the measurement and structural models. Through Confirmatory Factor Analysis (CFA), the reliability and validity of the latent constructs were assessed, followed by estimation of the structural paths to test the hypothesized relationships among variables. The combined use of SPSS and AMOS enabled a robust analysis of both measurement quality and theoretical model fit, thereby strengthening the credibility of the study's findings.

Prior to the main SEM analysis, several preliminary data screening and diagnostic procedures were conducted to ensure the quality and suitability of the dataset. First, a missing value analysis was performed to identify incomplete responses and assess the extent of missing data. Given the online survey design, cases with substantial missing values were excluded, while the overall level of missing data was found to be minimal.

Second, outlier detection was carried out to identify both univariate and multivariate outliers. Univariate outliers were examined through standardized scores, whereas multivariate outliers were assessed using the Mahalanobis distance criterion. This procedure ensured that extreme observations did not unduly influence parameter estimates in the SEM analysis.

Third, key assumptions underlying multivariate analysis were evaluated. Normality was assessed by examining skewness and kurtosis values for each observed indicator, while linearity among variables was inspected to confirm the appropriateness of the modeling approach. These assumption checks provided confidence that the data were suitable for SEM estimation.

Fourth, descriptive statistical analyses were conducted to summarize participants' demographic characteristics and cultural background variables. These statistics offered contextual insight into the sample composition and supported interpretation of the empirical findings.

Finally, Cronbach's alpha coefficients were calculated as an initial assessment of internal consistency reliability for each construct. This step ensured that the measurement items demonstrated acceptable reliability prior to further validity testing through confirmatory factor analysis.

Confirmatory Factor Analysis (CFA) was conducted to evaluate the construct validity of the measurement model and to ensure that the observed indicators adequately represented their respective latent variables. Several established criteria were applied to assess convergent validity, reliability, and overall model adequacy.

First, factor loadings were examined to determine the strength of the relationships between observed indicators and their corresponding constructs. Loadings of 0.50 or higher were considered acceptable, with values of 0.70 or above preferred to indicate strong indicator reliability. Second, composite reliability (CR) values of 0.70 or higher were used to confirm the internal consistency of each construct beyond Cronbach's alpha. Third, average variance extracted (AVE) values of at least 0.50 were required to demonstrate that each construct captured a sufficient proportion of variance from its indicators, thereby supporting convergent validity.

In addition to evaluating individual constructs, overall model fit was assessed using multiple goodness-of-fit indices. Acceptable fit was indicated by a chi-square to degrees of freedom ratio (χ^2/df) of 3.00 or below, a Comparative Fit Index (CFI) and Tucker–Lewis Index (TLI) of 0.90 or higher, and Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR) values of 0.08 or lower. These indices collectively provided evidence of how well the proposed measurement model fit the observed data.

To assess discriminant validity, the Fornell–Larcker criterion was applied. Specifically, the square root of the AVE for each construct was required to exceed the corresponding inter-construct correlations. This comparison ensured that each latent variable was empirically distinct and captured a unique conceptual domain, thereby supporting the validity of the measurement model.

Structural Equation Modeling (SEM) was employed to examine the hypothesized causal relationships among the latent constructs specified in the research model. In particular, the structural model tested the direct effects of attitude toward honest behavior (ATB), subjective norms (SN), and perceived behavioral control (PBC) on behavioral intention (BI), as well as the effects of behavioral intention (BI) and perceived behavioral control (PBC) on actual honest academic behavior (AB).

The evaluation of the structural model was based on several key statistical criteria. Standardized path coefficients (β) were examined to assess the strength and direction of the relationships between constructs. The critical ratio (CR) was used to determine whether each path coefficient differed significantly from zero, while p-values were compared against a significance threshold of .05 to establish statistical support for the hypothesized relationships. In addition, explained variance (R^2) values for behavioral intention and actual behavior were calculated to assess the model's explanatory power.

To further evaluate the stability and robustness of the structural relationships, a bootstrapping procedure with 5,000 resamples was conducted. This non-parametric approach allowed for the estimation of indirect effects and provided bias-corrected confidence intervals, thereby enabling a more rigorous assessment of mediation effects and enhancing confidence in the reliability of the SEM results.

To minimize the potential impact of common method bias, this study implemented both procedural and statistical remedies in accordance with established methodological recommendations.

Procedural remedies were applied during the questionnaire design and data collection stages. These included ensuring respondent anonymity to reduce social desirability bias, randomizing the order of questionnaire items to limit response pattern effects, and using clear and neutral wording to avoid leading or ambiguous statements. Together, these measures were intended to encourage honest responses and reduce systematic measurement error associated with self-reported data.

In addition to procedural controls, statistical remedies were employed to assess the presence of common method bias empirically. First, Harman's single-factor test was conducted, with results indicating that no single factor accounted for more than 50% of the total variance, suggesting that common method bias was unlikely to be a serious concern. Second, a Common Latent Factor (CLF) test was performed in AMOS to further examine the extent of shared variance attributable to the measurement method. The results of the CLF analysis provided additional evidence that common method bias did not significantly influence the observed relationships among the study variables.

This study was conducted in strict accordance with established ethical standards for social science research. Participation in the study was entirely voluntary, and respondents were informed of their right to withdraw at any stage without penalty. Prior to completing the questionnaire, all participants were provided with a clear explanation of the study's purpose and procedures and were required to give their informed consent.

To protect participants' privacy, all data were treated with strict confidentiality and were used exclusively for academic and research purposes. No personally identifiable information was collected, ensuring that individual responses could not be traced back to specific participants. The questionnaire was carefully designed to avoid sensitive, coercive, or potentially harmful content, thereby minimizing any risk of psychological discomfort or ethical concern.

Ethical approval and research procedures followed relevant institutional guidelines and best practices for responsible research conduct, consistent with widely accepted ethical principles in social science research (Resnik, 2020).

RESULT AND DISCUSSION

This chapter reports the empirical results of the study derived from data collected from 375 Indonesian undergraduate students enrolled in non-engineering programs. The analyses encompass descriptive statistics, preliminary data screening procedures, evaluation of the measurement model through Confirmatory Factor Analysis (CFA), and assessment of the structural model, including hypothesis testing, examination of indirect effects, and tests for common method bias. All analytical steps were conducted in accordance with established guidelines for Structural Equation Modeling (SEM) as recommended in the literature (Hair et al., 2019; Kline, 2016).

Descriptive Statistics

Respondent Profile

A total of 375 valid responses were obtained and included in the final analysis. The participants represented a wide range of non-engineering academic disciplines, including the social sciences, business and management, humanities, education, communication studies, psychology, and law. This disciplinary diversity reflects the broad academic backgrounds of the respondents and enhances the relevance of the findings for understanding academic honesty across writing-intensive fields within Indonesian higher education.

The demographic profile of the respondents is summarized in Table 1, which presents the distribution of participants by gender, study program, and region of origin. This overview highlights the heterogeneity of the sample and provides important context for interpreting the empirical findings.

Table 1. Demographic Characteristics of Respondents (N = 375)

Variable	Category	%
Gender	Female	62.4
	Male	37.6
Study Program	Social Sciences	21.1
	Business/Economics	19.7
	Education	16.8
	Psychology	14.9
	Law	11.5
	Communication	9.9
	Humanities	6.1
Region	Java	48.5
	Sumatra	16.3
	Kalimantan	9.1
	Sulawesi	10.7
	Bali–Nusa Tenggara	7.5
	Maluku–Papua	7.9

Sources: Analysis phase

Overall, the table indicates that the sample is dominated by female students and includes participants from a broad range of non-engineering disciplines and geographic regions across Indonesia, supporting the representativeness of the data for the study's objectives.

Preliminary Data Screening

Missing Data and Outliers

An initial examination of the dataset indicated that the proportion of missing values was minimal, with no variable exceeding the 5% threshold commonly considered acceptable in quantitative research. Given the limited extent of missing data, mean substitution was applied to a small number of cases to preserve the overall sample size and maintain statistical power, without introducing substantial bias.

In addition, an assessment of multivariate outliers was conducted using the Mahalanobis distance criterion. This analysis identified seven cases that exceeded the recommended cutoff value. However, these observations were retained in the dataset, as further inspection revealed no evidence of data entry errors or response patterns that would undermine their validity. Moreover, the inclusion of these cases was theoretically justified, as they reflected plausible variations in students' academic behavior and experiences. Retaining these observations allowed the analysis to capture the natural diversity present in the population while preserving the integrity of the empirical model.

Normality Assessment

An assessment of univariate normality was conducted by examining the skewness and kurtosis values for all observed indicators. The results showed that skewness and kurtosis values ranged from -1.28 to $+1.02$, which fall well within the commonly accepted thresholds for normal distribution in SEM analyses. These values indicate that the data did not exhibit substantial asymmetry or excessive peakedness, suggesting that the assumption of univariate normality was satisfactorily met. Consequently, the distributional characteristics of the data were considered appropriate for subsequent confirmatory factor analysis and structural equation modeling procedures.

Reliability (Cronbach's Alpha)

Before proceeding to the evaluation of the measurement and structural models, the internal consistency reliability of each construct was assessed to ensure that the items within each scale consistently measured the same underlying concept. Cronbach's alpha coefficients were calculated for all latent variables, as this statistic is widely used to evaluate the reliability of multi-item measurement instruments in behavioral research. Values exceeding the recommended threshold of 0.70 indicate satisfactory reliability, while higher values suggest stronger internal consistency among the indicators.

Table 2. Internal Consistency Reliability of Constructs

Construct	Cronbach's α
ATB	0.88
SN	0.85
PBC	0.87
BI	0.93
AB	0.83

Sources: Analysis phase

As shown in Table 2, all constructs exhibited strong internal consistency, with Cronbach's alpha values ranging from 0.83 to 0.93. These results indicate that the measurement items for each construct were reliable and suitable for further analysis using confirmatory factor analysis and structural equation modeling.

Measurement Model (CFA)

Factor Loadings

The results of the confirmatory factor analysis indicated that all observed indicators loaded significantly onto their respective latent constructs. Specifically, all factor loadings were statistically significant at the $p < .001$ level, demonstrating strong relationships between the measurement items and the underlying constructs they were intended to represent. In addition, each loading met or exceeded the minimum recommended threshold of 0.50, indicating adequate indicator reliability and supporting the convergent validity of the measurement model. These findings suggest that the selected items were appropriate and effective measures of their corresponding theoretical constructs, thereby providing a solid foundation for subsequent structural model testing.

Table 3. Factor Loading Ranges

Construct	Loading Range
ATB	0.64 – 0.81
SN	0.59 – 0.79
PBC	0.62 – 0.86
BI	0.66 – 0.89
AB	0.57 – 0.80

Sources: Analysis phase

Convergent Validity (CR and AVE)

Further evidence of convergent validity was provided through the assessment of composite reliability (CR) and average variance extracted (AVE) for each latent construct. All CR values met or exceeded the recommended threshold of 0.70, indicating a high level of internal consistency and confirming that the indicators reliably represented their respective constructs. In addition, all AVE values were greater than or equal to 0.50, demonstrating that each construct accounted for at least half of the variance in its observed indicators.

Together, these results confirm adequate convergent validity of the measurement model, suggesting that the items within each construct were not only consistent but also sufficiently correlated to capture the intended theoretical concepts. This provides further support for the robustness of the measurement model and justifies proceeding with the evaluation of the structural relationships among the constructs.

Table 4. CR and AVE

Construct	CR	AVE
ATB	0.90	0.58
SN	0.87	0.54
PBC	0.89	0.56
BI	0.94	0.63
AB	0.84	0.52

Sources: Analysis phase

Discriminant Validity

Discriminant validity was assessed using the Fornell–Larcker criterion to ensure that each latent construct was empirically distinct from the others included in the model. The analysis revealed that, for every construct, the square root of the average variance extracted (AVE) exceeded the corresponding inter-construct correlation coefficients. This finding indicates that each construct shared more variance with its own indicators than with other constructs in the model.

These results provide strong evidence of discriminant validity, confirming that the constructs measured conceptually different aspects of students' psychological determinants and academic behavior. Consequently, the measurement model demonstrates adequate construct separation, supporting the validity of subsequent structural analyses and hypothesis testing.

Table 5. AVE vs. Shared Variance

Construct	ATB	SN	PBC	BI	AB
ATB	**0.58**	0.33	0.30	0.44	0.27
SN	0.33	**0.54**	0.31	0.38	0.26
PBC	0.30	0.31	**0.56**	0.37	0.29

BI	0.44	0.38	0.37	**0.63**	0.41
AB	0.27	0.26	0.29	0.41	**0.52**

Sources: Analysis phase

In the discriminant validity matrix, the diagonal elements represent the square root of the Average Variance Extracted (AVE) for each construct, while the off-diagonal elements display the squared correlations between pairs of constructs. This matrix structure allows for a direct comparison between the variance captured by each construct and the variance it shares with other constructs. When the diagonal values exceed the off-diagonal values in the corresponding rows and columns, it indicates that each construct is more strongly related to its own indicators than to other latent variables, thereby providing empirical support for discriminant validity within the measurement model.

Model Fit (Measurement Model)

The overall fit of the measurement model was evaluated using multiple goodness-of-fit indices commonly recommended in Structural Equation Modeling. These indices provide a comprehensive assessment of how well the proposed model corresponds with the observed data. The results of the model fit evaluation are presented in Table 6., along with the recommended cutoff values for acceptable model fit.

Table 6. Fit Indices

Fit Index	Recommended	Obtained
χ^2/df	≤ 3.00	1.91
CFI	≥ 0.90	0.958
TLI	≥ 0.90	0.949
RMSEA	≤ 0.08	0.049
SRMR	≤ 0.08	0.041

Sources: Analysis phase

Overall, the results indicate that the measurement model demonstrates a good fit to the data. All obtained values meet or exceed the recommended thresholds, suggesting that the proposed factor structure adequately represents the observed relationships among the indicators and supports the suitability of the model for subsequent structural analysis.

Structural Model (SEM)

Structural Model Fit

Before testing the hypothesized structural relationships, the overall fit of the structural model was evaluated to determine how well the proposed theoretical framework aligned with the observed data. Model fit assessment is a critical step in Structural Equation Modeling, as it provides evidence that the estimated relationships among constructs are both statistically sound and theoretically meaningful. The results of the structural model fit evaluation are presented in Table 7.

Table 7. Structural Model Fit Indices

Fit Index	Value
χ^2/df	1.97
CFI	0.955
TLI	0.946
RMSEA	0.051
SRMR	0.044

Sources: Analysis phase

Overall, the fit indices reported in Table 7 indicate that the structural model demonstrates a strong and acceptable fit to the data. The chi-square to degrees of freedom ratio (χ^2/df) is well below the recommended threshold of 3.00, suggesting a good balance between model complexity and explanatory power. Similarly, the Comparative Fit Index (CFI) and

Tucker–Lewis Index (TLI) both exceed the commonly accepted cutoff of 0.90, indicating that the proposed model provides a substantial improvement over a null or independence model.

In addition, the Root Mean Square Error of Approximation (RMSEA) and the Standardized Root Mean Square Residual (SRMR) fall below the recommended maximum values of 0.08, reflecting a low level of approximation error and minimal residual differences between the observed and estimated covariance matrices. Taken together, these results provide strong evidence that the structural model adequately represents the underlying relationships among the constructs. This satisfactory model fit supports the validity of proceeding with hypothesis testing and interpretation of the estimated path coefficients within the proposed TPB-based framework.

Hypothesis Testing

Path Coefficients

This subsection presents the results of the structural path analysis conducted to test the hypothesized relationships among the latent variables in the proposed model. Path coefficients were estimated using Structural Equation Modeling (SEM) to evaluate both the strength and direction of the causal relationships specified in the Theory of Planned Behavior framework. Standardized regression weights (β) are reported to facilitate interpretation and comparison across paths, while statistical significance was assessed using p-values with a conventional threshold of .05.

Table 8. Structural Path Estimates

Hypothesis	Path	β	p-value	Result
H1	ATB → BI	0.38	< .001	Supported
H2	SN → BI	0.31	< .001	Supported
H3	PBC → BI	0.24	.001	Supported
H4	BI → AB	0.61	< .001	Supported
H5	PBC → AB	0.12	.028	Supported

Sources: Analysis phase

The results presented in Table 8 indicate that all hypothesized relationships were statistically significant and supported by the data. Attitude toward honest behavior (ATB) demonstrated the strongest effect on behavioral intention (BI), suggesting that students' personal evaluations of academic honesty play a central role in shaping their intention to act ethically. Subjective norms (SN) also exerted a substantial positive influence on BI, highlighting the importance of social expectations and perceived approval from significant others in guiding ethical intentions. Perceived behavioral control (PBC) showed a positive and significant, albeit comparatively smaller, effect on BI, indicating that students' confidence in their ability to behave honestly contributes to their intention formation.

Furthermore, behavioral intention emerged as the strongest predictor of actual honest academic behavior (AB), with a large standardized coefficient, underscoring its pivotal role as the immediate antecedent of ethical action. In addition to its indirect effect through BI, perceived behavioral control also exhibited a direct and significant influence on actual behavior, suggesting that students who feel capable of managing academic demands are more likely to translate ethical intentions into honest academic practices. Collectively, these findings provide strong empirical support for the applicability of the Theory of Planned Behavior in explaining academic honesty among non-engineering students in AI-mediated learning environments.

Variance Explained (R^2)

The explanatory power of the structural model was further evaluated by examining the coefficient of determination (R^2) for the endogenous variables, namely behavioral intention (BI) and actual honest behavior (AB).

The R^2 value for behavioral intention (BI) was 0.52, indicating that attitude toward honest behavior (ATB), subjective norms (SN), and perceived behavioral control (PBC) jointly explain 52% of the variance in students' intentions to behave honestly. This level of explained variance is considered substantial in behavioral and social science research, suggesting that the three TPB antecedents provide a strong and meaningful explanation of intention formation in the context of AI-mediated academic environments.

Similarly, the R^2 value for actual honest behavior (AB) was 0.48, meaning that behavioral intention (BI) and perceived behavioral control (PBC) together account for 48% of the variance in students' self-reported honest academic behavior. This finding indicates that nearly half of the variability in actual ethical conduct can be explained by students' intentions and their perceived ability to act honestly, reflecting a high level of predictive accuracy for the proposed model.

Overall, these R^2 values demonstrate the strong predictive power of the TPB-based structural model and are consistent with prior TPB research, which often reports moderate to high explained variance for intention and behavior. The results reinforce the suitability of TPB for understanding academic honesty among non-engineering students, particularly in learning environments where AI tools present both opportunities and ethical challenges.

Indirect Effects

To examine the presence and strength of indirect effects within the proposed model, a bootstrapping procedure with 5,000 resamples was conducted. Bootstrapping is a robust, non-parametric method that allows for the estimation of indirect effects and their statistical significance without relying on normality assumptions, making it particularly suitable for mediation analysis in SEM.

The results indicate that all indirect pathways from the TPB antecedents to actual honest academic behavior (AB) through behavioral intention (BI) were statistically significant. Specifically, the indirect effect of attitude toward honest behavior (ATB) on AB via BI was positive and significant ($\beta = 0.23$, $p < .001$), demonstrating that students' positive evaluations of honesty influence their actual behavior primarily by strengthening their intention to act honestly. Similarly, the indirect path from subjective norms (SN) to AB through BI was also significant ($\beta = 0.19$, $p < .001$), suggesting that perceived social expectations shape honest academic behavior by first influencing students' intentions.

In addition, perceived behavioral control (PBC) exhibited a significant indirect effect on AB through BI ($\beta = 0.15$, $p < .01$). This finding indicates that students' confidence in their ability to behave honestly enhances their ethical behavior partly by reinforcing their intention to do so. However, because PBC also demonstrated a significant direct effect on AB in the structural model, its influence on actual behavior is only partially mediated by BI.

Overall, these results show that behavioral intention plays a central mediating role in the TPB framework. It fully mediates the effects of attitude toward honest behavior and subjective norms on actual honest behavior, while partially mediating the effect of perceived behavioral control. In practical terms, this means that students' ethical attitudes and perceived social expectations translate into honest academic conduct primarily through a strong internal intention, whereas perceived capability not only shapes intention but also directly facilitates ethical action.

Summary of Findings

The principal findings of this study can be summarized as follows. First, attitude toward honest behavior (ATB), subjective norms (SN), and perceived behavioral control (PBC) were found to significantly influence students' intentions to engage in honest academic practices. Second, behavioral intention (BI) emerged as the strongest and most consistent predictor of actual honest academic behavior in AI-supported learning environments. Third, perceived behavioral control demonstrated both indirect effects through behavioral intention and a direct influence on honest behavior, highlighting the importance of students' perceived capability in translating ethical intentions into action.

Fourth, the proposed TPB-based model accounted for a substantial proportion of variance in both behavioral intention (52%) and actual honest behavior (48%), indicating strong explanatory power. Fifth, the Structural Equation Modeling results showed an excellent overall model fit and confirmed the reliability and validity of the measurement instruments. Finally, these findings provide robust empirical evidence that psychological and social determinants continue to play a critical role in sustaining academic honesty among non-engineering students, even in educational contexts where AI tools are widely accessible and easily misused.

This study aimed to examine the psychological determinants of honest academic behavior among Indonesian non-engineering students in AI-supported learning environments by applying the Theory of Planned Behavior (TPB). The findings provide strong empirical support for the applicability of TPB in explaining academic honesty within contemporary higher education contexts characterized by widespread access to generative AI tools.

First, the results demonstrate that attitude toward honest behavior (ATB) significantly influences students' behavioral intention to act honestly. This finding underscores the central role of personal moral evaluations in shaping ethical intentions, particularly in non-engineering disciplines where academic tasks rely heavily on subjective interpretation, writing, and critical reasoning. When students perceive honesty as personally valuable and morally important, they are more likely to commit to ethical academic conduct, even in the presence of AI tools that offer convenient shortcuts.

Second, subjective norms (SN) were found to exert a strong and positive effect on behavioral intention. This result highlights the importance of social influence in shaping ethical intentions, especially within Indonesia's collectivist cultural context. Perceived expectations from peers, lecturers, and the broader academic environment appear to reinforce norms of academic integrity, suggesting that honesty is not solely an individual choice but also a socially embedded behavior.

Third, perceived behavioral control (PBC) significantly predicted behavioral intention and also demonstrated a direct effect on actual honest behavior. This dual influence indicates that students who feel capable of managing academic demands, such as time pressure, workload, and writing complexity, are more likely to both intend to behave honestly and to translate those intentions into action. In AI-rich learning environments, this finding is particularly important, as students with low self-efficacy may be more tempted to rely on AI tools unethically when they perceive academic tasks as overwhelming.

Consistent with TPB theory, behavioral intention (BI) emerged as the strongest predictor of actual honest academic behavior. The mediation analysis further revealed that BI fully mediates the effects of attitude and subjective norms, and partially mediates the effect of perceived behavioral control. This pattern confirms that ethical behavior in academic settings is largely intention-driven, while also acknowledging that perceived capability can directly facilitate or constrain honest conduct.

Overall, the model explains a substantial proportion of variance in both behavioral intention and actual behavior, indicating strong explanatory power. These findings extend prior TPB research by demonstrating that psychological and social determinants remain highly relevant in regulating academic honesty, even as AI technologies fundamentally reshape how academic work is produced.

CONCLUSION

This study empirically demonstrates that the Theory of Planned Behavior (TPB) robustly predicts honest academic behavior among Indonesian non-engineering students in AI-mediated environments, with attitude toward honesty, subjective norms, and perceived behavioral control shaping behavioral intentions, which primarily drive actual behavior. Despite generative AI's rise, ethical decisions hinge on internal moral evaluations, social expectations, and self-efficacy rather than technology alone, bolstered by Indonesian cultural norms like local wisdom (though not statistically modeled). Practically, universities should prioritize fostering positive attitudes, integrity norms, and academic self-efficacy via ethical AI literacy, redesigned assessments, and supportive instruction over mere detection. For future research, longitudinal studies could test TPB's predictive validity over time, incorporating cultural values (e.g., *gotong royong*) as mediators and comparing engineering vs. non-engineering cohorts to refine AI integrity interventions.

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