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The Role of Indonesian Local Wisdom in Shaping Male Students' Academic Honesty in the Age of AI Tools

B.M.A.S. Anaconda Bangkara
Universitas Presiden, Indonesia
Email: anaconda@president.ac.id

Abstract *This study investigates the factors that encourage Indonesian male university students to maintain academic honesty despite the growing accessibility of AI tools that can be misused for cheating. Grounded in the Theory of Planned Behavior (TPB), the research examines the relationships between attitude toward honest behavior (ATB), subjective norms (SN), perceived behavioral control (PBC), behavioral intention (BI), and actual honest behavior (AB). Data were collected through an online survey of 350 male undergraduate students across Indonesia who had experience using generative AI tools such as ChatGPT, QuillBot, or Perplexity. Structural Equation Modeling (SEM) with AMOS was employed to analyze the measurement and structural models. Results show that all TPB paths are statistically significant: ATB, SN, and PBC each positively influence BI, which in turn strongly predicts AB. The model demonstrated excellent fit (CFI = .992, RMSEA = .017, CMIN/DF = 1.095). Beyond psychological determinants, Indonesian cultural values—such as honesty, trustworthiness, responsibility, and sense of shame—appear to reinforce students' motivation to uphold integrity, even when AI-enabled shortcuts are convenient and difficult to detect. The study extends TPB applications by shifting the focus from explaining cheating to understanding the drivers of honesty. It offers practical implications for designing integrity policies, educational programs, and AI-related guidelines that are both ethically grounded and culturally responsive.*

Keywords: *Academic Honesty; Artificial Intelligence (AI) tools; Theory of Planned Behavior (TPB); Indonesia Male University Students.*

INTRODUCTION

The rapid development of artificial intelligence tools, such as ChatGPT, Perplexity, QuillBot, and other generative systems, has reshaped the academic landscape in significant ways (Belwal, 2025; Raheem et al., 2023). These technologies offer clear advantages, from faster access to information to enhanced writing support and more efficient learning processes (Kasneci et al., 2023; Susnjak, 2023). However, their rapid rise has also brought new concerns, particularly regarding academic integrity.

As AI-generated writing becomes increasingly indistinguishable from human work, some students may feel tempted to use these tools in ways that circumvent genuine learning. Examples include completing assignments, taking exams, or conducting research with minimal personal effort. This challenge is not confined to one country; educators around the world have noted a growing number of academic misconduct cases linked to AI misuse (Cotton et al., 2023; Dwivedi et al., 2023; Rudolph et al., 2023).

Despite these risks, many university students, especially male students in Indonesia, continue to demonstrate honest academic behavior even when AI-based shortcuts are readily available. This raises an important and often overlooked question: What motivates these students to remain honest in an era when unethical options are easier, faster, and increasingly difficult to detect? While a substantial body of research examines why students cheat, far fewer studies focus on the positive factors that encourage students to avoid misconduct and uphold academic integrity (Brien & Cowton, 2021; McCabe et al., 2012).

Indonesia presents a particularly compelling context for exploring this issue. Beyond formal academic rules, students are raised within cultural traditions and moral frameworks that strongly shape their choices. Elements of Indonesian local wisdom, such as *jujur* (honesty), *amanah* (trustworthiness), *malu* (a culturally rooted sense of shame), *gotong royong* (collective responsibility), and strong family-centered values, play a vital role in shaping young people's behavior and ethical decision-making (Koentjaraningrat, 2015; Rahardjo, 2019; Subagya, 2020). These cultural norms create social environments where integrity is not simply a personal virtue but a shared community expectation.

Within this cultural setting, male students may also encounter a unique combination of social and psychological expectations. Research in Indonesia shows that men are frequently expected to show responsibility, leadership, and moral strength—traits associated with local masculinity norms such as *tepo seliro* (self-restraint), *tata krama* (proper conduct), and *tenggang rasa* (consideration for others) (Magnis-Suseno, 1997; Purwadi & Rahyono, 2021). These expectations can reinforce a stronger commitment to academic honesty, even when AI-enabled shortcuts are easily accessible.

In a context where sophisticated AI tools coexist with deeply rooted cultural values, Indonesia becomes an especially meaningful setting for understanding why some students continue to choose honesty over convenience, even when opportunities for misconduct are increasingly abundant (Arifianto, 2023; Hidayat, 2022).

This study aims to explore why some Indonesian male university students choose to remain honest in their academic work despite the availability of AI-based tools that could facilitate cheating. Existing research primarily focuses on understanding dishonesty, including why students cheat and the factors that promote unethical behavior (McCabe et al., 2012; Curtis et al., 2018). However, there is less focus on understanding why some students resist the temptation to cheat. This research gap is significant, particularly in the context of AI tools that offer new challenges for academic integrity (Stephens, 2019).

This study specifically addresses several gaps in the literature. First, most studies do not focus on male students, even though research shows gender differences in academic integrity behaviors (Whitley et al., 1998; Teixeira & Rocha, 2008). Second, the Theory of Planned Behavior (TPB), which has been applied to understand cheating behavior, has rarely been used to explore why students decide to stay honest, especially with the advent of AI tools (Beck & Ajzen, 1991; Stone et al., 2009). Third, the role of cultural context and local wisdom in shaping academic honesty has been largely overlooked, despite calls for incorporating non-Western perspectives in academic integrity research (Retnowati, 2019; Emmerich & Peucker, 2017). Finally, while research on AI tools as avenues for academic misconduct is emerging, more empirical studies are needed in this area (Cotton et al., 2023; Kasneci et al., 2023).

The TPB, which explains behavior through attitude toward the behavior (ATB), subjective norms (SN), and perceived behavioral control (PBC), serves as the theoretical foundation for this study (Ajzen, 1991). The TPB suggests that a student's intention to engage in honest behavior is shaped by how they view honesty (ATB), the pressure or support they feel from others (SN), and their confidence in resisting temptations like AI tools (PBC). This model is ideal for examining academic honesty because it integrates personal values with the social and cultural environment, which influences student behavior.

This study aims to fill the research gaps by investigating how these psychological and cultural factors influence academic honesty among Indonesian male students. The specific objectives are to examine how attitudes, subjective norms, and perceived control influence students' intentions to stay honest, and how these intentions lead to actual honest behavior.

Additionally, the research will explore how Indonesian cultural values shape these intentions and behaviors. Through this, the study contributes to the academic integrity literature by shifting the focus from why students cheat to why some choose to act honestly. It also provides insights into how cultural expectations influence academic behavior, which is particularly valuable for creating culturally relevant integrity policies in higher education.

METHOD

This study adopted a quantitative, cross-sectional survey approach to investigate the factors that shape honest academic behavior among Indonesian male university students in the context of AI-enhanced learning. To analyze these relationships, Structural Equation Modeling (SEM) with AMOS was employed to validate both the measurement model and the structural pathways proposed by the Theory of Planned Behavior (TPB). SEM was chosen because it enables researchers to examine multiple latent variables at once, account for measurement error, and test complex causal relationships within a single analytical framework (Hair et al., 2019).

The study focused on male undergraduate students enrolled at universities across Indonesia. Using purposive sampling, 350 respondents were recruited, specifically targeting active students who had experience using AI tools such as ChatGPT, QuillBot, or Perplexity.

For SEM analyses involving complex models, a minimum sample size of around 200 participants is generally recommended (Kline, 2016). With 35 indicators and 5 latent variables, the final sample of 350 participants comfortably exceeds this guideline, providing strong statistical power for the analyses.

The questionnaire measured five latent constructs based on the Theory of Planned Behavior (TPB):

1. Attitude Toward Honest Behavior (ATB) – 6 items
2. Subjective Norms (SN) – 6 items
3. Perceived Behavioral Control (PBC) – 7 items
4. Behavioral Intention (BI) – 9 items
5. Actual Honest Behavior (AB) – 7 items

All items were rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The statements were adapted from well-established TPB and academic integrity instruments (Beck & Ajzen, 1991; Stone et al., 2010; McCabe et al., 2012) and were further adjusted to fit the context of ethical AI use in academic settings.

To strengthen content validity, the questionnaire was reviewed by experts, lecturers with backgrounds in educational psychology and research methodology, who assessed the relevance and clarity of each item.

Data were collected through an online questionnaire distributed via university groups, academic forums, and student associations. Participation was voluntary and anonymous. Respondents provided informed consent prior to participation, and no identifying information was recorded.

Data Screening

1. Missing Data

All responses were fully completed, and no missing values were found, so imputation was not required.

2. Normality Test

Univariate normality was evaluated through skewness and kurtosis critical ratios (CR), and all indicators fell within the acceptable ±2.58 range, confirming that univariate normality was met.

Multivariate normality was also supported, with a multivariate kurtosis value of −4.653 and a CR of −0.855, both well below the ±5 cutoff.

3. Outlier Detection

The Mahalanobis d-squared test flagged a few cases with higher values, but none surpassed the conservative cutoff of $p < 0.001$. Even the highest value ($d^2 = 60.047$, $p1 = 0.005$) remained within an acceptable range. Therefore, no multivariate outliers were excluded from the dataset.

4. Multicollinearity

A review of the sample covariance and correlation matrices showed that none of the correlations were excessively high (none exceeded 0.90). The condition numbers, which ranged from about 62 to 64, suggested that multicollinearity was within acceptable limits. Additionally, the covariance matrix remained positive definite once the model successfully converged.

Measurement Model (CFA Requirements)

A Confirmatory Factor Analysis (CFA) was conducted to carefully assess whether each construct in the model demonstrated adequate reliability and validity. This step allowed us to examine how well the observed indicators represented their underlying latent variables and to ensure that the measurement model met the expected psychometric standards.

1. Factor Loadings

All standardized factor loadings were above 0.50 and reached statistical significance ($p < .001$). This shows that each item contributed meaningfully to its intended construct and demonstrated solid reliability, reinforcing that the indicators were performing as expected within the measurement model.

2. Construct Reliability (CR) and Average Variance Extracted (AVE)

The Composite Reliability (CR) values for all constructs were higher than the commonly recommended cutoff of 0.70, while the Average Variance Extracted (AVE) values also exceeded the 0.50 benchmark. Together, these results indicate that the constructs showed strong convergent validity, meaning the items were consistently capturing the same underlying concept as suggested by Fornell and Larcker (1981)

3. Discriminant Validity

The square roots of the AVE values were larger than the correlations between each pair of constructs, indicating that every construct was more closely related to its own indicators than to other constructs. This pattern provides clear evidence of discriminant validity, showing that the constructs are distinct and not measuring the same underlying concept.

Structural Model (SEM Requirements)

SEM analysis was conducted in two stages:

1. Evaluation of model fit using chi-square, CFI, TLI, RMSEA, and other indices.
2. Estimation of structural paths testing the causal relationships among TPB constructs.

1. Fit Indices Criteria

Following Hair et al. (2019), acceptable thresholds were:

- CMIN/DF < 3
- CFI, TLI, IFI ≥ 0.90
- RMSEA ≤ 0.08 (≤ 0.05 = excellent)
- GFI, AGFI ≥ 0.90

2. Structural Model Evaluation

Once the model met the required fit criteria based on the various indices, the next step involved evaluating the structural model to examine the causal relationships among the TPB constructs. At this stage, the primary focus was on assessing the path coefficients, their statistical significance, and the magnitude of both direct and indirect effects connecting the latent variables.

This analysis provides insights into how Attitude Toward Honest Behavior, Subjective Norms, and Perceived Behavioral Control Influence Behavioral Intention, as well as how intention subsequently predicts Actual Honest Behavior. To determine the significance of these relationships, indicators such as Standardized Regression Weights, Critical Ratios (CR), and p-values were examined.

The structural model was also evaluated in terms of the variance explained (R^2) for the endogenous constructs. R^2 values help indicate how much of the variation in behavioral intention and actual honest behavior can be accounted for by the variables included in the model. Higher R^2 values reflect stronger explanatory power of the structural relationships.

Overall, this stage is essential for determining whether the empirical findings support the theoretical predictions of the TPB framework and whether the causal pathways proposed in the model are validated by the data.

Ethical Considerations

This study followed established ethical guidelines for research involving human participants. All respondents took part voluntarily and gave their informed consent after being told about the study's academic purpose and the confidentiality of their responses. No identifying personal information was collected, and their anonymity was fully protected throughout the entire process

Summary

This chapter has described the methodological steps used in the study, covering the sampling process, measurement instruments, data screening procedures, CFA, and the requirements for SEM. Overall, the data met the criteria for SEM analysis, as shown by acceptable levels of normality, the absence of outliers, reliable measurement items, and a sufficiently large sample. The following chapter will present the empirical findings from both the measurement model and the structural model.

RESULTS AND DISCUSSION

Overview

This chapter reports the empirical results derived from the measurement and structural models analyzed using Structural Equation Modeling (SEM) in AMOS. The presentation includes assessments of data normality, detection of potential outliers, tests of reliability and validity, evaluation of overall model fit, and hypothesis testing based on the Theory of Planned Behavior (TPB).

Assessment of Normality

1. Univariate Normality

Univariate normality was examined using skewness and kurtosis values expressed as critical ratios (CR). All 35 indicators showed CR values that fell within the recommended ±2.58 range, suggesting that each observed variable followed an acceptably normal distribution.

2. Multivariate Normality

AMOS produced a multivariate kurtosis value of −4.653 with a critical ratio (CR) of −0.855, both well below the cutoff of 5.0. These results indicate that the data comfortably meet the multivariate normality assumption needed for Maximum Likelihood (ML) estimation.

Conclusion**:**

The data satisfy both univariate and multivariate normality assumptions.

Detection of Multivariate Outliers

Multivariate outliers were assessed using Mahalanobis d-squared (d^2). The highest value identified was 60.047 (case 350) with a probability of p1 = 0.005. Since this value did not fall below the conservative cutoff of $p < 0.001$, none of the cases were considered outliers. As a result, all 350 responses were kept for the subsequent analyses.

Examination of Sample Moments, Covariances, and Correlations

The covariance and correlation matrices were reviewed to assess the stability of the data and to check for any signs of multicollinearity. All item variances were positive and fell within a reasonable range (0.60–0.78). None of the inter-item correlations exceeded 0.90, and the condition numbers, 62.738 for the covariance matrix and 64.507 for the correlation matrix, suggest that multicollinearity is not an issue. In addition, the covariance matrix remained positive definite once the model converged. Overall, these results indicate that the dataset is statistically appropriate for both CFA and SEM analyses.

Model Convergence (Minimization History)

The minimization history in AMOS showed that the early iterations included a few negative eigenvalues, which is typical at the start of the estimation process. By the fourth iteration, these negative eigenvalues had disappeared. The fit function then stabilized by iteration 10 with a final value of F = 602.414. The final ratio reached 1.000, indicating successful convergence, and the condition number (134) remained within an acceptable range. Taken together, these results confirm that the model converged properly and produced stable, reliable parameter estimates.

Measurement Model Evaluation (CFA)

A Confirmatory Factor Analysis was carried out to evaluate how well each item measured its intended construct and to determine whether the overall constructs demonstrated solid reliability and validity. This step allowed us to verify that the measurement model functioned as expected and that the indicators consistently represented the underlying theoretical concepts.

1. Standardized Factor Loadings

All 35 indicators loaded significantly ($p < .001$) on their respective constructs, with standardized loadings above 0.50 and most exceeding 0.70.

2. Construct Reliability and Convergent Validity

This section presents the results of the construct reliability and convergent validity assessments. These analyses were conducted to ensure that each latent construct is measured consistently and that the indicators meaningfully capture the underlying concepts they are intended to represent. The summary of CR and AVE values for all constructs is shown in the table below:

Table 1. Construct Reliability

Construct	CR	AVE	Status
ATB	> 0.80	> 0.50	Valid
SN	> 0.80	> 0.50	Valid
PBC	> 0.80	> 0.50	Valid
BI	> 0.85	> 0.50	Valid
AB	> 0.85	> 0.50	Valid

Sources: Analysis stage

3. Discriminant Validity

The square roots of the AVE values were greater than the correlations between constructs,

indicating that discriminant validity was achieved according to the Fornell–Larcker criterion
Conclusion:
The measurement model is valid and reliable.

Structural Model Fit
The structural model demonstrated outstanding fit across all categories, as follows.
1. Absolute Fit Indices

The absolute fit indices provide an initial overview of how well the proposed model reproduces the observed data. These indices focus on the overall discrepancy between the sample covariance matrix and the model-implied covariance matrix. The values obtained for each absolute fit index are summarized in Table 2.

Table 2. Absolute Fit Indices

Index	Value	Criteria	Evaluation
CMIN	602.414	—	—
df	550	—	—
p-value	0.060	> 0.05	Good
CMIN/DF	1.095	< 2.0	Excellent
RMR	0.026	< 0.05	Good
GFI	0.914	> 0.90	Good
AGFI	0.901	> 0.90	Good

Sources: Analysis stage

2. Incremental Fit Indices

Incremental fit indices were examined to evaluate how much better the proposed model fits the data compared to a baseline model with no relationships among variables. These indices assess model improvement by considering additional parameters, and higher values generally indicate a more well-specified model. The results of the incremental fit indices are summarized in Table 3 below.

Table 3. Incremental Fit Indices

Index	Value	Criteria	Status
NFI	0.919	> 0.90	Good
RFI	0.912	> 0.90	Good
IFI	0.992	> 0.95	Excellent
TLI	0.992	> 0.95	Excellent
CFI	0.992	> 0.95	Excellent

Sources: Analysis stage

3. RMSEA

The Root Mean Square Error of Approximation (RMSEA) was further examined to assess the degree of approximation error in the model. RMSEA and its associated confidence interval provide additional evidence regarding the closeness of fit between the proposed model and the population covariance structure. The RMSEA-related statistics are presented below.

Table 4. RMSEA

Index	Value	Criteria	Status
RMSEA	0.017	—	—
LO 90	0.000	—	—
HI 90	0.025	—	—
PCLOSE	1.000	—	—

Sources: Analysis stage

These results indicate that the model demonstrates an excellent level of close fit.

4. Parsimony Fit Indices

Parsimony fit indices were assessed to evaluate how efficiently the model explains the data relative to the number of parameters estimated. These indices help determine whether the model achieves a good balance between fit quality and model simplicity. The values for the parsimony indices are summarized in the table below.

Table 5. Parsimony Fit Indices

Index	Value
PRATIO	0.924
PNFI	0.850
PCFI	0.917

Sources: Analysis stage

The three indices shown in the table, **PRATIO**, **PNFI**, and **PCFI** are used to evaluate whether the SEM model is not only well-fitting but also **efficient** in terms of the number of parameters it uses. In other words, they help determine whether the model achieves a good balance between accuracy and simplicity.

1. PRATIO = 0.924

This value indicates that **92.4% of the possible parameters in the baseline model are utilized in the final model**.

- Higher values (closer to 1) are generally preferred.
- This suggests that the model represents the data in a relatively "economical" way.

2. PNFI = 0.850

PNFI adjusts the Normed Fit Index (NFI) by taking parsimony into account.

- A value of 0.850 indicates that the model has a **strong balance between goodness-of-fit and parsimony**.
- Higher values imply more efficient use of parameters without sacrificing model fit.

3. PCFI = 0.917

PCFI is the parsimony-adjusted version of the CFI.

- A value of 0.917 shows that the model is **highly efficient while still demonstrating excellent fit quality**.
- Values above 0.80 are typically considered strong.

5. Information Criteria

Information criteria were examined to evaluate the model's predictive capability and parsimony relative to alternative models. These indices compare the proposed model with both the saturated model and the independence model, where lower values generally indicate a better balance between model fit and complexity. The information criteria values are presented below.

Table 6. Information Criteria

Index	Value
AIC	762.414
BIC	1071.049
ECVI	2.185

Sources: Analysis stage

The lower AIC, BIC, and ECVI values indicate that the proposed model has better predictive capability and a more efficient structure compared to both the saturated and independence models. In other words, the proposed model is the most optimal because it offers the best balance between model fit and complexity.

6. Model Stability

Model stability was further assessed using the Hoelter critical N values, which estimate the minimum sample size required for the model to be considered reliable. Higher Hoelter values indicate a more stable and well-supported model. The stability results are presented below.

- Hoelter (.05) = 351
- Hoelter (.01) = 366

These values demonstrate that the structural model is highly stable and well-supported by the available sample. Combined with the previous fit indices, the results confirm that the structural model exhibits excellent overall fit.

Structural Path Analysis (Hypothesis Testing)

The structural path analysis was conducted to examine the causal relationships proposed in the Theory of Planned Behavior (TPB). Using the regression weights generated from the SEM model, each hypothesized pathway was tested for statistical significance to determine whether the theoretical predictions were supported by the data. The results of the hypothesis testing are presented below.

Table 7. Structural Path Analysis

Path	Estimate (β)	p-value	Result
ATB → BI	Significant	< .001	Supported
SN → BI	Significant	< .001	Supported
PBC → BI	Significant	.001	Supported
BI → AB	Significant	< .001	Supported

Sources: Analysis stage

All structural paths were statistically significant, indicating that all four hypotheses within the TPB framework were supported. Attitude Toward Honest Behavior, Subjective Norms, and Perceived Behavioral Control each showed significant positive effects on Behavioral Intention, and Behavioral Intention significantly predicted Actual Honest Behavior.

Interpretation:

1. Attitude is a strong predictor of intention, so that students with positive moral attitudes are more likely to remain honest.
2. Subjective norms influence intention, so that family, peers, and lecturers shape expectations of integrity.
3. Perceived behavioral control helps students resist AI misuse and maintain self-regulation.
4. Intention strongly drives actual honest behavior.

Modification Indices

Modification Indices (MI) were reviewed to explore whether any adjustments could meaningfully improve the model. A few correlated error terms and cross-loadings showed MI values in the range of 4 to 15, but none approached the more critical threshold of 20 or above. Moreover, the suggested modifications did not align with the theoretical structure of the TPB, so no changes were made to the mode.

Decision:

The model was retained without modifications to preserve theoretical purity.

Summary of Findings

This section summarizes the key empirical findings derived from the SEM analyses. Each point below highlights the main outcomes of the data screening, measurement evaluation, structural modeling, and hypothesis testing, providing a concise overview of how well the model performed and how the TPB framework was supported in the context of academic honesty.

1. SEM assumptions were fully satisfied, including normality, absence of outliers, and no signs of multicollinearity.
2. The measurement model demonstrated strong psychometric quality, with high levels of convergent and discriminant validity as well as solid reliability.
3. The structural model achieved excellent overall fit, supported consistently by all major model fit indices.
4. All hypothesized relationships in the TPB framework were confirmed, showing strong and significant causal links as predicted.
5. Behavioral intention emerged as the strongest determinant of students' actual honest behavior.
6. Psychological factors and social influences played a crucial role in shaping ethical behavior amid widespread availability of AI tools.

Overall, the findings present a coherent and well-supported model that explains how internal motivations and social influences shape honest behavior among students in an era where AI tools are increasingly accessible. The strength of the structural model and the consistency of the results reinforce the relevance of the Theory of Planned Behavior in understanding ethical decision-making. These insights provide a meaningful foundation for educators and institutions seeking to promote integrity and responsible AI use in academic settings.

Discussion

Attitude Toward Honest Behavior Influences Intention (H1)

The findings indicate that students' attitudes have a clear and positive effect on their intention to act honestly. This supports TPB's central idea that when individuals hold favorable evaluations of a behavior, they are more motivated to carry it out (Ajzen, 1991). In this case, when students view honesty as something valuable—whether academically, morally, or personally—they become more inclined to uphold ethical conduct in their studies.

This result is consistent with earlier studies showing that students' moral judgments about cheating and academic misconduct play a major role in shaping their ethical intentions (Simkin & McLeod, 2010; Stone et al., 2010). Students who feel personally responsible or morally obligated to behave ethically are much more likely to avoid dishonest practices.

Indonesian Context: Local Values Supporting Attitude

In the Indonesian context, values such as *jujur* (honesty), *amanah* (trustworthiness), and *tanggung jawab* (responsibility) are deeply rooted and introduced from a young age. Male students, in particular, often experience additional social expectations that associate responsibility and integrity with maturity and strong character. These cultural influences can reinforce their positive attitudes toward honest behavior and highlight the importance of integrity within academic life

Subjective Norms Influence Intention (H2)

The findings also showed that subjective norms play a significant role in shaping students' intentions. When students believe that people who matter to them, such as friends, lecturers, parents, or community figures, expect them to act honestly, they are more inclined to form intentions that align with those expectations.

This result is consistent with prior research showing how social norms influence academic integrity (Beck & Ajzen, 1991; Passow et al., 2006). In collectivistic settings like Indonesia, social expectations tend to carry even greater weight, and going against group norms can trigger feelings of guilt or *malu* (shame).

Indonesian Context: Collectivism and Social Pressure

Indonesian society tends to be collectivistic, placing strong importance on social harmony and personal reputation (Hofstede, 2001). Cultural principles such as *tepo seliro* (self-restraint), *tata krama* (proper conduct), *sopan santun* (politeness), and *malu* (avoidance of shame) help create an environment where dishonest behavior is viewed not only as academically inappropriate but also socially embarrassing. These cultural values amplify the influence of subjective norms, making students more inclined to behave honestly because they want to uphold social expectations and avoid bringing shame to themselves or their community.

Perceived Behavioral Control Influences Intention (H3)

Perceived behavioral control (PBC) was also found to have a significant positive influence on students' intentions. This suggests that when students feel confident in their ability to resist the unethical use of AI tools, they are more likely to develop strong intentions to behave honestly. This aligns with Ajzen's (1991) view that PBC functions much like self-efficacy, shaping a person's belief in their ability to carry out the behaviors they value.

This result is also consistent with earlier research showing that PBC can predict ethical or prosocial intentions, particularly in situations where opportunities or temptations to cheat are present (Whiteside & Lynam, 2001).

Indonesian Context: Self-Regulation and Moral Resilience

Culturally, Indonesian students are often raised with strong teachings about self-control and resilience, reinforced through family, religious, and community environments. Values such as *pengendalian diri* (self-regulation), *amanah* (trustworthiness), and *akhlak baik* (good moral character) may help strengthen their sense of capability to act honestly even when tempting shortcuts exist. This cultural foundation likely contributes to higher levels of perceived behavioral control among male students.

Behavioral Intention Predicts Actual Honest Behavior (H4)

Behavioral intention emerged as the strongest predictor of actual honest behavior, reinforcing TPB's core idea that intention is the most direct and influential driver of what people ultimately do. Students who are genuinely motivated and committed to upholding academic integrity are far more likely to consistently act honestly in practice.

This result aligns well with the broader TPB literature, which has repeatedly shown strong links between intention and behavior across various areas, including ethics, health, environmental actions, and academic integrity (Ajzen, 2011; Beck & Ajzen, 1991).

Indonesian Context: Translating Intention into Behavior

In Indonesia, cultural values such as *konsistensi moral* (moral consistency), *harga diri* (self-worth), and *martabat* (personal dignity) often encourage people to act in ways that match their intentions. For male students in particular, there can be a strong sense of obligation to follow through on their commitments, as demonstrating responsibility and trustworthiness is highly valued within societal expectations for men.

The Role of AI in Academic Integrity

Even though AI tools were not included as a formal variable in the model, they form an important part of the study's context. The findings indicate that psychological factors—such as attitudes, social expectations, and perceived behavioral control, can help students resist the temptations and convenience offered by AI-based academic tools.

Students who possess strong moral values, feel socially accountable, and believe in their ability to regulate their actions are far less likely to misuse AI, even when the chances of being caught are low. This shows that the presence of advanced technology does not automatically weaken academic integrity when individuals have solid internal motivation and supportive social environments.

Integration With Local Wisdom

Local wisdom presents a culturally meaningful layer for interpreting the findings:

- Honesty: Reinforces attitude
- Collectivism & social harmony: Amplify subjective norms
- Self-restraint: Supports self-control and PBC
- Shame: Discourages dishonest behavior
- Responsibility: Facilitates intention–behavior consistency

These cultural values offer a meaningful perspective for understanding Indonesian students' honesty in a more complete and nuanced way.

Comparison With Previous Studies

The results of this study align with a wide range of international research that has used the TPB to predict ethical and academic behaviors. Nonetheless, this study adds to the existing literature by:

1. Focusing on positive behavior (honesty) instead of misconduct.
2. Examining this behavior in the context of AI-based opportunities for cheating.
3. Incorporating Indonesian cultural values into the interpretation.
4. Using a large and statistically robust sample analyzed through SEM.

Summary

The findings provide strong evidence that the TPB framework effectively predicts honest behavior among male students in Indonesia. Attitude, subjective norms, and perceived behavioral control each contributed meaningfully to the formation of behavioral intention, which then emerged as a significant predictor of students' actual actions.

In addition, Indonesian cultural values seem to strengthen these psychological factors, offering a solid basis for ethical academic behavior even in a time when AI tools are widely available

CONCLUSION

This study investigated factors promoting academic honesty among Indonesian male university students amid accessible AI tools, applying the Theory of Planned Behavior (TPB) via Structural Equation Modeling (SEM) in AMOS. Results confirmed strong TPB pathways: attitude toward honesty (ATB), subjective norms (SN) from peers/family/lecturers/community, and perceived behavioral control (PBC) over AI temptations significantly predicted behavioral intention (BI), which in turn strongly drove actual honest behavior (AB), with excellent model fit (CFI = .992, RMSEA = .017, CMIN/DF = 1.095). These psychological elements proved resilient against AI-enabled shortcuts, bolstered by Indonesian cultural values like honesty, trustworthiness, responsibility, sense of shame, and collective responsibility in a collectivistic context. By shifting focus from cheating to honesty drivers, the findings enrich academic integrity research in tech-cultural intersections. For future research, longitudinal studies could track how evolving AI tools (e.g., multimodal generative systems) interact with these factors over time, or comparative analyses across genders and regions to test cultural universality.

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