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Research Article

The Effect of Ethical Anxiety, Ethical Risk Perception, and Ethical Awareness on Students' Academic Performance Through the Use of Generative AI

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Abstract: This study analyzes the influence of Ethical Anxiety, Ethical Risk Perception, and Ethical Awareness on students' Academic Performance, with the use of Generative AI as a mediating variable. The method employed is quantitative, using the SEM-PLS approach with 41 questionnaire items. The results indicate that the instruments are valid and reliable, with R-squared values of 0.727 for Generative AI Usage and 0.705 for Students' Academic Performance. Surprisingly, Ethical Anxiety and Ethical Risk Perception have a significant positive effect on Generative AI Usage, which partially mediates their impact on Academic Performance. However, mediation does not occur in the relationship between Ethical Awareness and Academic Performance. These findings suggest that ethical factors play an important role, but their influence on AI usage and its impact on academic outcomes is not uniform within the academic environment.

Keywords: Ethical Anxiety; Ethical Awareness; Ethical Risk Perception; Generative AI Usage; SEM-PLS; Students Academic Performance

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1. Introduction

The rapid development of generative Artificial Intelligence (AI), such as ChatGPT, has transformed the way students learn. This technology enhances efficiency (Mahdi et al., 2023) but also raises ethical risks, such as plagiarism and reduced originality in thinking (Sutedjo et al., 2025). Academic performance, typically measured by GPA, does not fully reflect students' critical thinking abilities and academic integrity (Gandasari et al., 2024). Surveys by Populix (2023) and Lumban Gaol & Manalu (2023) indicate that most students have used AI for coursework, yet many do not verify the accuracy of results or consider ethical aspects (Hasibuan & Sayekti, 2024).

Dependence on AI has the potential to diminish reasoning skills and academic responsibility (Zamir & Sultana, 2024), suggesting that the primary issue lies not in the technology itself, but in the psychological and moral factors of its users. Based on Ethical Decision-Making Theory (Rest, 1986), three ethical factors—ethical anxiety, ethical risk perception, and ethical awareness—are expected to influence how students use AI. Generative AI usage acts as a mediating variable bridging these ethical factors and students' academic performance. AI usage accompanied by ethical awareness has been shown to improve learning quality (Diantama, 2023; Aisyah et al., 2024), whereas usage without ethical consideration reduces conceptual understanding.

This study was conducted in Sleman Regency, Yogyakarta, a hub of academic activity with diverse levels of digital literacy (LLDIKTI V, 2024). The study proposes a new model integrating the three ethical variables to explain their impact on academic performance through AI usage as a mediator, aiming to strengthen educational policies that are ethical and adaptive to technology (Khalifa & Albadawy, 2024).

2. Preliminaries or Related Work or Literature Review

2.1 Academic Motivation Theory

According to Deci and Ryan in the Self-Determination Theory (Vansteenkiste et al., 2006), academic motivation is classified into intrinsic and extrinsic types. Intrinsic motivation drives learning due to interest and understanding, whereas extrinsic motivation arises from pressure or rewards. Studies indicate that intrinsic motivation enhances academic performance (Annamalai et al., 2025), while extrinsic motivation can reduce it. In the context of generative AI, this theory explains that the way students use AI reflects their type of motivation and influences learning outcomes.

2.2 Ethical Decision-Making Theory

According to Rest (1986), ethical decision-making consists of four stages: ethical awareness, ethical judgment, ethical intention, and ethical behavior (Yang et al., 2025; Usher & Barak, 2024). In the context of generative AI, this theory explains how ethical awareness, risk perception, and ethical anxiety influence students' behavior when using the technology (Benke & Szőke, 2024). High ethical anxiety can impair moral judgment (Zhu et al., 2024), while balanced awareness and risk perception promote responsible AI usage (Hsiao & Tang, 2024). Integrating this theory with academic motivation shows that ethical factors help shape AI usage behavior, which in turn impacts students' performance (Annamalai et al., 2025).

2.3 Generative AI Usage

Generative AI usage refers to students' behavior in utilizing technologies such as ChatGPT for academic activities, reflecting the moral behavior stage in Ethical Decision-Making Theory (Mumtaz et al., 2025). Usage patterns are influenced by ethical awareness, risk perception, and ethical anxiety (Zhu et al., 2024). Based on Self-Determination Theory, intrinsic motivation encourages reflective and ethical AI usage, whereas extrinsic motivation tends to result in superficial behavior (Annamalai et al., 2025). Students with high ethical awareness are more prudent in using AI responsibly (Tan & Maravilla, 2024; Yang et al., 2025). Therefore, AI usage behavior serves as an important mediator bridging ethical factors and students' academic performance..

2.4 Students' Academic Performance

Students' academic performance reflects the success of the learning process, measured not only by grades but also by critical thinking, problem-solving skills, and academic integrity (Tsai, 2024). Performance results from the interaction of personal, social, and institutional factors. In the digital era, performance assessment includes various forms such as projects, portfolios, and learning analytics, reflecting an active and dynamic learning approach (Wong et al., 2024).:

2.5 Ethical Anxiety in AI Usage

Ethical anxiety refers to the concern when using AI that may violate moral values or academic integrity. Students with high ethical anxiety tend to be more cautious and ethical in using AI (Zhu et al., 2024; Hsiao & Tang, 2024). However, excessive anxiety can hinder adaptation to technology (Chen et al., 2024). Based on Moral Emotion Theory, this anxiety functions as a moral control over deviant behavior (Curtis, 2023) and is an important aspect in maintaining academic honesty in the digital era (Salsabila, 2024).

2.6 Ethical Risk Perception in AI Usage

According to Perceived Risk Theory, high risk perception makes students more cautious in using AI (Wu et al., 2022). This awareness aligns with the anti-plagiarism regulation

Permendiknas No. 17 of 2010 and reflects efforts to uphold academic integrity in the digital era (Zhu et al., 2024).

3. Proposed Method

This study employed a quantitative method with a descriptive and associative approach to describe the variables and examine the influence of ethical anxiety, ethical risk perception, and ethical awareness on academic performance, with generative AI usage as a mediating variable. Data were collected through a survey questionnaire. The research was conducted in Sleman Regency, Yogyakarta, involving students from various public and private universities, with data collection carried out from May to August 2025. The population consisted of 256,208 active students in higher education institutions in Sleman (BPS DIY, 2024). Yogyakarta was selected due to its status as a national hub for higher education, with high technological access and a heterogeneous student population. The sample size was determined using the Krejcie and Morgan (1970) table at a 5% significance level and 95% confidence level, resulting in a minimum of 384 respondents representing the population. Data were obtained using questionnaires as primary data and academic reports from Universitas Negeri Yogyakarta as secondary data.

4. Results and Discussion

Analysis Using SEM-PLS with SmartPLS, including validity, reliability, inter-variable relationships, and hypothesis testing.

1. **Outer Model Test (Measurement Model)**

The outer model test was conducted to ensure that the indicators are valid and reliable in measuring the latent constructs (Ethical Anxiety, Ethical Risk Perception, Ethical Awareness, Generative AI Usage, and Students' Academic Performance) through tests of convergent validity, discriminant validity, and reliability.

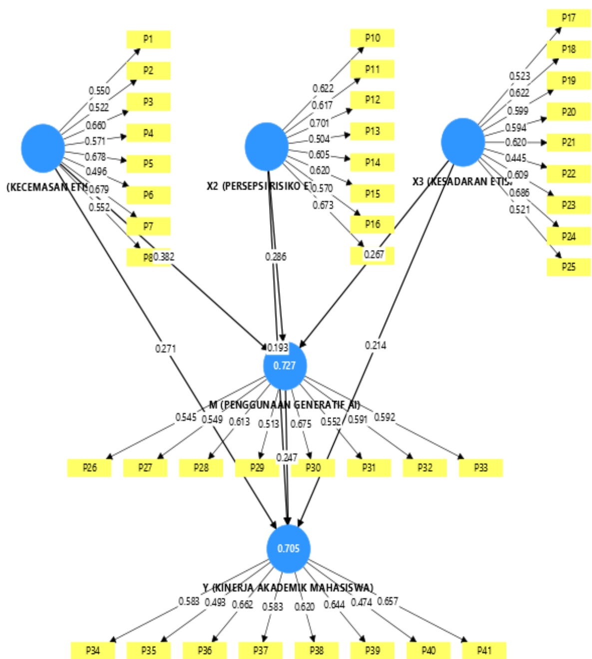


Figure 1. Measurement Model Results (SmartPLS Output)

1) **Convergent Validity**

Based on Figure 2 above, all indicators have loading factors greater than 0.40 (Hair et al., 2019), although most remain below the ideal value of 0.70, resulting in a relatively low AVE value. However, since the Composite Reliability values exceed 0.70 and the study is exploratory in nature, all indicators were retained, with a note on the limitation in convergent validity.

2) **Discriminant Validity**

As shown in Figure 2 above, the discriminant validity test was conducted using cross-loading, Fornell-Larcker criteria, and HTMT. The cross-loading results indicate that each indicator has a higher correlation with its respective construct, thus meeting this criterion. However, the Fornell-Larcker and HTMT criteria were not fully met because the inter-construct correlations exceeded the square root of AVE, and HTMT values were greater than 0.90. This suggests conceptual overlap among ethical variables. Nevertheless, the model was retained as the construct reliability was acceptable, and the PLS approach is prediction-oriented.

3) **Construct Reliability**

Based on Figure 2 above, all constructs (X1, X2, X3, M, Y) show CA, rho_A, and CR values greater than 0.70, indicating good reliability. Although convergent and discriminant validity were not fully achieved, the analysis was continued with caution in interpreting the results.

2. Multicollinearity Test (VIF)

The VIF test was conducted to ensure that there is no high correlation among indicators or independent variables. According to Hair et al. (2021), a model is considered free from multicollinearity if the VIF value is less than 5.0. The results show that all VIF values fall below this threshold, indicating that the data are free from multicollinearity.

Table 1. Multicollinearity Test Results (VIF)

Indicators	VIF
P1	1.503
P2	1.492
P3	1.659
P4	1.397
P5	1.579
P6	1.224
P7	1.508
P8	1.347
P9	1.534
P10	1.496
P11	1.487
P12	1.632
P13	1.554
P14	1.582
P15	1.613
P16	1.527
P17	1.297
P18	1.440

Indicators	VIF
P19	1.531
P20	1.652
P21	1.725
P22	1.473
P23	1.711
P24	1.839
P25	1.671
P26	1.395
P27	1.522
P28	1.452
P29	1.205
P30	1.595
P31	1.459
P32	1.598
P33	1.510
P34	1.538
P35	1.255
P36	1.628
P37	1.528
P38	1.545
P39	1.606
P40	1.415
P41	1.634

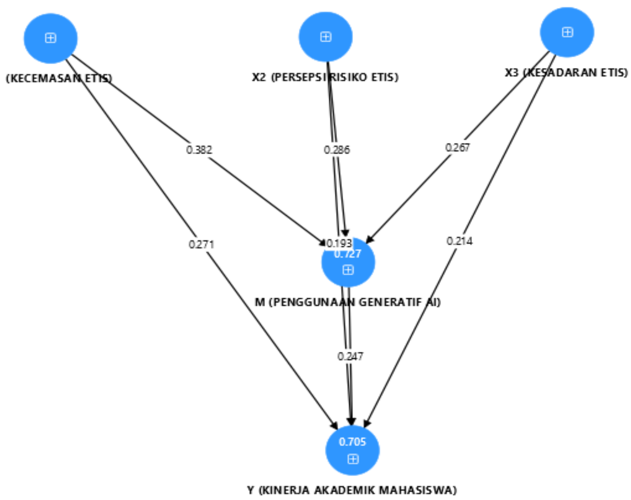
Source: Primary data processed with SmartPLS (2025)

Based on Table 1 above, the VIF values for all indicators (ranging from 1.205 to 1.839) are well below the threshold of 5, indicating that there is no multicollinearity issue within the model. This finding demonstrates that each indicator is able to explain its respective latent variable independently, without excessive dependence on other indicators. Therefore, the research instrument is considered valid and suitable for use in the subsequent structural model (inner model) analysis.

3. **Inner Model Test (Structural Model)**

The inner model test aims to evaluate the relationships among latent constructs and to assess the influence of independent variables on dependent variables, as well as the overall strength of the research model.

Figure 3. Structural Model Test Results



1) **Coefficient of Determination (R^2)**

Based on Figure 3 above, the R^2 values indicate the extent to which the independent variables explain the dependent variables. According to Table 19, the R^2 value for construct M is 0.727 and for construct Y is 0.705, both of which fall into the strong category (Hair et al., 2021). This means that the model is capable of explaining more than 70% of the data variance, indicating that it is suitable for further analysis.

2) **Effect Size (f^2)**

As shown in Figure 3 above, most relationships among the constructs exhibit small effects ($f^2 < 0.15$), except for the path X1 → M, which shows a moderate effect ($f^2 = 0.204$). This indicates that X1 contributes a relatively strong influence on M, whereas the other variables have relatively smaller effects on their respective constructs.

3) **Predictive Relevance (Q^2)**

Based on Figure 3 above, the Q^2 values for construct M (0.711) and Y (0.666) are both greater than 0.35, which places them in the strong category. This implies that the model has good predictive relevance for the endogenous variables and is appropriate for subsequent analytical stages.

4. Hypothesis Testing

Hypothesis testing was conducted using the bootstrapping procedure in SmartPLS, with the criteria of *t*-statistic > 1.96 and *p*-value < 0.05 (α = 5%). A hypothesis is accepted if it meets these criteria. The complete results are presented in the following table.

Table 2. Hypothesis testing

Relation	Original sample (O)	T statistics (|O/STDEV|)	P values	Description
M → Y	0.247	2.414	0.016	Hypothesis Accepted
X1 → M	0.382	5.560	0.000	Hypothesis Rejected
X1 → Y	0.271	3.438	0.001	Hypothesis Accepted
X2 → M	0.286	4.254	0.000	Hypothesis Rejected
X2 → Y	0.193	2.265	0.024	Hypothesis Accepted
X3 → M	0.267	3.442	0.001	Hypothesis Accepted
X3 → Y	0.214	2.302	0.021	Hypothesis Accepted

Source: Processed Data, SmartPLS (2025)

Based on Table 2 above, the analysis results indicate that two initial hypotheses (H1 and H2) were rejected because the direction of their effects contradicted the predicted relationships, although they were statistically significant. Ethical Anxiety (X1) and Ethical Risk Perception (X2) unexpectedly exerted a positive influence on Generative AI Usage (M). Conversely, H3 and H4 were accepted as they aligned with the predictions: Ethical Awareness (X3) positively affected M, and M positively influenced Academic Performance (Y). Overall, variables X1, X2, and X3 demonstrated significant direct effects on Y, forming the foundation for the subsequent mediation analysis.

Table 3. Hypothesis Testing Results (Indirect Effects)

Relation	Original Sampel (O)	T Statistics	P Value	Description
X1 → M → Y	0.094	2.250	0.024	Hypothesis Accepted
X2 → M → Y	0.071	1.970	0.049	Hypothesis Accepted
X3 → M → Y	0.066	1.930	0.054	Hypothesis Rejected

Source: Processed Data, SmartPLS (2025)

. Based on Table 3 above, Generative AI Usage was found to be a partial mediator in the relationships between Ethical Anxiety (H5) and Ethical Risk Perception (H6) with Students' Academic Performance, as both indirect effects were significant. This indicates that AI usage strengthens the influence of these two ethical variables on students' performance. However, in the case of Ethical Awareness (H7), the indirect effect through AI was not significant, implying that this variable does not function as a mediator in the relationship.

5. **Dynamics of the Influence of Ethical Anxiety and Risk on AI Usage (H1 and H2 Rejected)**
   The significant positive effects of X1 and X2 on M contradict the initial predictions (Zhu et al., 2024). According to Moral Emotion Theory (Haidt, 2007) and Perceived Risk Theory (Cunningham, 1967), anxiety or perceived risk can lead to more cautious and regulated behavior rather than avoidance, which explains the higher M scores. This reversed direction of influence may be attributed to contextual factors or the operationalization of the AI usage construct (M).
6. **The Constructive Role of Ethical Awareness (H3 Accepted)**
   The positive influence of X3 on M aligns with Ethical Decision-Making Theory (Rest, 1986). Conceptually, high ethical awareness functions as a "moral compass," encouraging thoughtful and responsible AI usage. This finding is consistent with Zhu et al. (2024) and Hsiao & Tang (2024), who emphasize that ethical awareness enhances self-regulation and prudent decision-making in technology utilization.
7. **The Impact of AI Usage on Perceived Academic Performance (H4 Accepted)**
   The positive effect of M on Y reflects students' perception of improved academic performance through AI usage. This result is consistent with Academic Motivation Theory and the findings of Wecks et al. (2024), suggesting that AI tools may enhance engagement and productivity. However, it also points to the possibility of an "illusion of competence" (as noted in Chapter I) and highlights the contextual relevance of inequality issues (Gandasari et al., 2024) in shaping students' perceived benefits.
8. **The Complexity of AI Usage as a Mediator (H5, H6 Accepted; H7 Rejected)**
   H5 and H6 were accepted, indicating that AI Usage partially mediates how Ethical Anxiety and Ethical Risk Perception (X1/X2) influence Academic Performance (Y). In this relationship, cautious AI usage strengthens students' perceived performance outcomes. Conversely, H7 was rejected, suggesting that Ethical Awareness (X3) affects academic performance through other internal mechanisms such as intrinsic motivation and personal standards rather than through AI usage alone. This underscores the fundamental impact of ethical awareness on students' learning approaches and self-regulated behavior.

5. Conclusions

H5 and H6 were accepted, demonstrating that Generative AI Usage serves as a partial mediator in the relationship between Ethical Anxiety and Ethical Risk Perception (X1/X2) with Academic Performance (Y). This finding suggests that students experiencing higher levels of ethical anxiety or perceived risk tend to engage with AI more cautiously and deliberately, which in turn enhances their perceived academic outcomes. Such results highlight that ethical tension does not necessarily inhibit technology adoption but can instead promote more mindful and responsible AI utilization that contributes positively to learning performance.

Conversely, H7 was rejected, indicating that Ethical Awareness (X3) does not exert a significant indirect effect through AI usage. Instead, it influences academic performance through internal mechanisms such as intrinsic motivation, moral reasoning, and personal standards. This implies that students with higher ethical awareness are likely guided by internalized values rather than external technological tools, reinforcing the notion that ethical consciousness fundamentally shapes students' learning approaches and self-regulated academic behavior beyond their interaction with AI systems.

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