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ACADEMIC FRAUD AND ARTIFICIAL INTELLIGENCE : A FRAUD DIAMOND THEORY PERSPECTIVE WITH MACHIAVELLIANISM AS MODERATOR

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ABSTRACT

This study aims to examine the influence of the Fraud Diamond dimensions—pressure, opportunity, rationalization, and capability—on academic fraud behavior, with the misuse of AI-generated content acting as a mediating variable. The research was conducted on students enrolled in the Corporate Financial Accounting study program at Politeknik Negeri Sambas. The sampling technique used was purposive sampling, targeting students who have taken or are currently taking the Professional and Business Ethics course. A total of 243 student responses were collected. This study employed a quantitative approach and utilized Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4 as the analytical tool. The findings show that pressure, capability, and rationalization significantly influence the misuse of AI-generated content, whereas opportunity does not. Additionally, pressure, opportunity, and capability have a direct effect on academic fraud behavior, while rationalization does not show a significant impact. The study also reveals that the misuse of AI-generated content does not mediate the relationship between the Fraud Diamond dimensions and academic fraud behavior. These results suggest that despite the availability of AI as a tool for academic misconduct, internal psychological and individual factors are more decisive in driving such behavior.

Keywords : Academic Fraud Behavior; AI-Generated Content; Fraud Diamond Theory; Machiavellianism; PLS-SEM

ABSTRAK

Penelitian ini bertujuan untuk mengkaji pengaruh dimensi Fraud Diamond—tekanan, peluang, rasionalisasi, dan kapabilitas—terhadap perilaku kecurangan akademik, dengan penyalahgunaan konten yang dihasilkan oleh AI sebagai variabel mediasi. Penelitian ini dilakukan pada mahasiswa Program Studi Akuntansi Keuangan Perusahaan di Politeknik Negeri Sambas. Teknik pengambilan sampel yang digunakan adalah purposive sampling, dengan target mahasiswa yang telah atau sedang menempuh mata kuliah Etika Profesi dan Bisnis. Sebanyak 243 respon mahasiswa berhasil dikumpulkan. Penelitian ini menggunakan pendekatan kuantitatif dan menganalisis data dengan metode Partial Least Squares Structural Equation Modeling (PLS-SEM) menggunakan alat bantu SmartPLS 4. Hasil penelitian menunjukkan bahwa tekanan, kapabilitas, dan rasionalisasi berpengaruh signifikan terhadap penyalahgunaan konten AI, sedangkan peluang tidak berpengaruh. Selain itu, tekanan, peluang, dan kapabilitas memiliki pengaruh langsung terhadap perilaku kecurangan akademik, sementara rasionalisasi tidak menunjukkan pengaruh yang signifikan. Penelitian ini juga mengungkapkan bahwa penyalahgunaan konten AI tidak memediasi hubungan antara dimensi Fraud Diamond dan perilaku kecurangan akademik. Temuan ini menunjukkan bahwa meskipun AI tersedia sebagai alat untuk melakukan pelanggaran akademik, faktor psikologis internal dan karakter individu lebih menentukan dalam mendorong terjadinya perilaku tersebut.

Kata Kunci : Perilaku Kecurangan Akademik; Konten yang Dihasilkan AI; Teori Fraud Diamond; Machiavellianisme; PLS-SEM

INTRODUCTION

Academic dishonesty has become an increasingly alarming issue in higher education, particularly with the advancement of technology that introduces tools such as artificial intelligence (AI). This phenomenon undermines academic integrity, damages the reputation of educational institutions, and contributes to the emergence of an unethical professional generation. Forms of dishonesty such as plagiarism, data fabrication, and unauthorized collaboration have become more complex with the rise of generative AI technologies.

The theoretical framework employed in this study is the Fraud Diamond Theory, introduced by Wolfe & Hermanson (2004). This model expands upon the classic Fraud Triangle by adding a fourth element—capability—thus encompassing pressure, opportunity, rationalization, and capability as the four key factors driving individuals to commit fraud (Basmar & Sulfati, 2022). In the educational context, pressure originates from academic demands and psychological burdens faced by students (Abdullah, 2024), while opportunity and capability are amplified by widespread access to AI technologies.

A novel dimension in the study of academic fraud is the misuse of AI-generated content, such as ChatGPT or similar tools. Students may use these technologies to draft essays, complete exams, or even fabricate research data (Reiter et al., 2025; Vieriu & Petrea, 2025). Using AI-generated content without proper attribution or understanding becomes a new form of plagiarism and information manipulation (Roe et al., 2023). In this study, AI misuse is modeled as a mediating variable that bridges the relationship between the Fraud Diamond factors and academic fraud behavior.

In addition to technological influences, individual psychological traits also shape the tendency to misuse AI. One significant personality trait is Machiavellianism—Machiavellianism is a personality trait that belongs to the Dark Triad, characterized by a cynical, manipulative attitude and a belief that the ends justify the means. Individuals with elevated scores on the Machiavellianism scale have a tendency to engage in deceptive and dishonest behaviors to attain their objectives and demonstrate a paucity of moral values (Elballah & Aljarboa, 2025). Individuals high in Machiavellianism are more likely to exploit any means necessary to achieve their academic goals, including misusing AI, often justified through rational self-serving logic. In the current study, Machiavellianism serves as a moderating variable, potentially strengthening the relationship between AI misuse and academic fraud (Barbaranelli et al., 2018).

Previous research has shown that individuals with high levels of Machiavellianism are more vulnerable to unethical behavior, and when combined with technological capabilities such as AI, the likelihood of academic fraud increases (Reiter et al., 2025) . Therefore, mapping the interaction between personality factors and technological misuse is crucial in understanding academic dishonesty among university students.

According to a report by Rong et al. (2024) , approximately 86% of students have used AI in their academic activities, with many of them unaware that such usage may violate academic ethics. In a notable case in the United States in 2024, a psychology student was apprehended for using ChatGPT to produce a complete fieldwork report, including fabricated data and fictitious references undetected by plagiarism software (Miao et al., 2024). Upon further investigation, the student scored high on the Mach-IV scale, indicating a high level of Machiavellianism, and used rationalizations such as “everyone else is doing it” and “I’m just being efficient with technology” as moral justifications. This case illustrates how academic pressure, technical capability, access to AI tools, rationalization, and Machiavellian traits can collectively create an ecosystem conducive to AI-assisted academic fraud.

The novelty of this study lies in the development and empirical testing of a new conceptual model that integrates the elements of the Fraud Diamond Theory—namely pressure, opportunity, rationalization, and capability—with academic fraud behavior, by introducing the misuse of AI-generated content as a mediating variable. In addition, this research introduces a novel contribution by incorporating Machiavellianism as a moderating variable in the relationship between AI misuse and academic fraud. While prior studies have examined academic fraud through isolated psychological or technological lenses, very few have explored their combined interaction within a comprehensive fraud-based theoretical framework, especially in the context of higher education. The proposed model is tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4, allowing for a robust analysis of both mediation and moderation effects within a predictive, theory-building context.

The purpose of this study is to investigate the complex interplay between the components of Fraud Diamond Theory, the misuse of AI-generated content, Machiavellian personality traits, and academic fraud behavior among students. By constructing an integrated theoretical model and empirically analyzing each variable, this research seeks to provide a deeper understanding of the multifaceted drivers of academic dishonesty in the age of artificial intelligence.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Fraud Diamond Theory

The Fraud Diamond Theory, introduced by (Wolfe & Hermanson, 2004) , expands the traditional Fraud Triangle by adding a fourth element—capability—alongside pressure, opportunity, and rationalization. Recent studies have applied this framework to academic settings, particularly in understanding digital cheating and AI misuse. Safitri et al. (2023) found that rationalization and capability significantly influence academic fraud behavior among students during online learning, highlighting the role of students' technical skills and cognitive justifications. Similarly, (Warni & Margunani, 2022) showed that pressure, opportunity, rationalization, and the misuse of information technology positively impact academic dishonesty, although capability showed no significant effect in their study. In the context of AI, Chan (2023) explored students' perceptions of "AI-giarism" and revealed a nuanced view, where students reject overt AI-generated plagiarism but express ambivalence toward subtler forms of AI use, suggesting a need for clearer ethical guidelines. Together, these findings confirm the relevance of the Fraud Diamond Theory in analyzing academic misconduct in the digital era.

Pressure

Pressure is the first element in the fraud diamond theory that drives individuals to commit fraudulent acts. Academic pressure may include demands for high grades, heavy workloads, time constraints, or fear of failure. In the context of advancing AI technology, academic pressure increasingly pushes students to seek shortcuts in completing academic tasks. Alshurafat et al. (2024) in their study on factors influencing the misuse of ChatGPT among accounting students, found that all fraud triangle components, including pressure, are significant determinants of academic dishonesty and ChatGPT misuse. Pressure acts as a strong driving factor for students to use AI-generated content without proper attribution, especially when they feel compelled to complete academic assignments under pressure (Alamanda et al., 2024).

H1a: Pressure influences Misuse of AI-Generated Content

Academic pressure has been proven to directly influence academic dishonesty. Research involving students shows that both academic pressure and academic capability affect fraudulent behavior (Miranda et al., 2023). Anggraini et al. (2024) , in their study on the influence of the fraud pentagon on academic misconduct, found that pressure has a positive impact on academic dishonesty. This suggests that the greater the pressure faced by students, the higher the likelihood of engaging in dishonest practices. An analysis of the fraud triangle's influence on academic dishonesty among accounting students also found that pressure, opportunity, and rationalization have a positive and significant impact on academic fraud. Empirical findings suggest that as pressure increases, so does fraudulent activity (Kusumayanti & Utama, 2024).

H1b: Pressure influences Misuse of AI-Generated Content

Opportunity

Opportunity refers to the conditions that enable fraudulent behavior to occur. In the academic context, this includes weak supervision, lenient policies, or the absence of effective detection methods. The advancement of AI technologies like ChatGPT has created new opportunities for academic dishonesty. Alshurafat et al. (2024) found that opportunity is a significant determinant of ChatGPT misuse among students. The ease of access and use of AI technology increases the likelihood that students will misuse AI-generated content for academic purposes. Fraudulent behavior involving AI is influenced by multiple factors, including opportunity (Alamanda et al., 2024). In the era of remote learning and digital education, opportunities to commit academic fraud using AI have increased, particularly as detection systems often fail to identify AI-generated content (Rahardyan et al., 2024).

H2a: Opportunity influences Misuse of AI-Generated Content

Opportunity has a direct influence on students' academic dishonesty. Prior studies have found that opportunity has a positive and significant effect on academic fraud (Kusumayanti & Utama, 2024) . The more opportunities that are present, the higher the likelihood that students will engage in dishonest behavior. Warni & Margunani (2022) found that opportunity is one of the elements of the fraud diamond that positively affects academic dishonesty among students. Opportunities arising from weak oversight and the ease of accessing various online information sources contribute to the likelihood of academic fraud. Empirical evidence from studies examining the fraud diamond and GONE theory confirms that opportunity positively influences academic fraud behavior, indicating that increased opportunities are associated with higher rates of misconduct (Neva & Amyar, 2021).

H2b: Opportunity influences Academic Fraud Behavior

Capability

Capability refers to the skills and individual characteristics that enable a person to commit fraudulent acts. In the context of AI use, technical skills in operating and leveraging AI technologies become a crucial factor. Students with greater understanding and proficiency in using AI have a higher capability to misuse AI-generated content. Studies by Chan & Tsi (2023) and (Mohammadkarimi, 2023) found that easy access and mastery of AI increase students' tendency toward plagiarism and academic dishonesty. In these studies, educators agreed that AI amplifies the opportunities and appeal of academic fraud, particularly among students who can effectively utilize such technologies. Other research supports the view that individual ability in using technology significantly influences AI misuse for academic fraud (Alamanda et al., 2024; Harahap, 2024) . Students with stronger knowledge of AI functionality and the ability to manipulate AI outputs to avoid detection are more likely to engage in misuse of AI-generated content.

H3a: Capability influences Misuse of AI-Generated Content

Capability plays a direct role in academic fraud. Individuals with specific knowledge and skills have a greater potential to engage in dishonest academic behavior. Within the fraud diamond framework, capability is a key element that complements pressure, opportunity, and rationalization. Studies by Rachmawati et al. (2024), Utami & Purnamasari (2021) and (Artani & Wetra, 2017) confirm that capability significantly influences academic fraud among students.

H3b: Capability influences Academic Fraud Behavior

Rationalization

Rationalization is the psychological process through which individuals justify dishonest actions. In academic settings, students often rationalize the use of AI-generated content with statements such as "it's just for reference," "it's not plagiarism because it came from AI," or "everyone else is doing it.". The study by Alshurafat et al. (2024) confirmed that rationalization is a significant determinant of ChatGPT misuse among students. The stronger the rationalization, the greater the likelihood that students will misuse AI-generated content. Academic misconduct involving AI is influenced by various factors, including rationalization. Students tend to justify their use of AI for academic tasks with seemingly acceptable reasons that downplay the ethical implications. Savitri (2025) also found that rationalization positively affects academic dishonesty, reinforcing the notion that justification mechanisms play a crucial role in facilitating fraudulent behavior.

H4a: Rationalization influences Misuse of AI-Generated Content

Rationalization has a direct influence on academic fraud behavior. Previous studies have shown that rationalization significantly and positively affects academic dishonesty (Kusumayanti & Utama, 2024; Warni & Margunani, 2022) . The self-justification process and the minimization of the perceived seriousness of misconduct are key drivers of fraudulent behavior. Rachmawati et al. (2024) also found that rationalization positively affects academic fraud among students. These findings suggest that the stronger the rationalization held by students, the higher their tendency to commit academic fraud.

H4b: Rationalization influences Academic Fraud Behavior

Misuse of AI-Generated Content

The misuse of AI-generated content represents a new form of academic dishonesty in the digital era. Studies have shown that using tools like ChatGPT to write academic articles or complete closed-book examinations constitutes a form of academic misconduct (Rahardyan et al., 2024) . This reinforces the idea that the misuse of AI-generated content contributes directly to fraudulent academic behavior. Alshurafat et al. (2024) identified that the misuse of ChatGPT by accounting students is a key determinant of academic dishonesty. Utilizing AI technology without proper attribution or to bypass legitimate learning processes is a form of academic fraud. Improper use of information technology has been proven to significantly influence academic fraud behavior (Harahap, 2024; Kusumayanti & Utama, 2024) . As AI tools like ChatGPT continue to evolve, the risk of their misuse in academic contexts increases, heightening concerns over ethical behavior in education (Alamanda et al., 2024; Rahardyan et al., 2024).

H5: Misuse of AI-Generated Content influences Academic Fraud Behavior

Machiavellianism

Machiavellianism is a personality trait marked by manipulation, exploitation of others, and lack of moral conscience. In academic settings, highly Machiavellian individuals are more likely to misuse AI for dishonest purposes. Studies have shown that Machiavellian traits intensify the likelihood of academic fraud (Basri et al., 2023; Rachmawati et al., 2024; Setyaki et al., 2021) . Individuals with strong Machiavellian tendencies tend to disregard ethical and moral considerations in pursuit of academic success. As a personality trait centered on self-serving manipulation, Machiavellianism has the potential to strengthen the relationship between the misuse of AI-generated content and academic fraud behavior. Such individuals are more inclined to exploit AI technologies for personal gain without considering the ethical implications. In the context of rapidly advancing AI technologies and their potential misuse in academia, Machiavellianism emerges as a critical moderating factor that must be addressed—especially in the development of effective academic fraud prevention strategies involving AI.

H6: Machiavellianism strengthens the influence of Misuse of AI-Generated Content on Academic Fraud Behavior

The Fraud Diamond Theory—comprising pressure, opportunity, rationalization, and capability—offers a comprehensive framework for understanding fraudulent behavior, including in academic settings. Recent empirical studies confirm that these four dimensions significantly influence students' tendencies to engage in academic dishonesty. Warni & Margunani (2022) found that pressure, opportunity, and rationalization positively affect academic cheating, while capability showed no significant impact, suggesting that motivational and situational factors play a more dominant role. Herawaty & Masbirorotni (2022) further support this by demonstrating that each element of the Fraud Diamond significantly predicts dishonest academic behavior, particularly when mediated by the misuse of information technology. Similarly, Pratama et al. (2023) highlight how AI technology intensifies the effects of pressure, opportunity, and capability, reinforcing the model's relevance in digital learning environments. These findings collectively provide strong support for the hypothesis that the Fraud Diamond dimensions positively influence academic fraud behavior, especially in the context of modern technological tools.

H7a: Misuse of AI-generated content mediates the relationship between pressure and academic fraud behavior

H7b: Misuse of AI-generated content mediates the relationship between opportunity and academic fraud behavior

H7c: Misuse of AI-generated content mediates the relationship between capability and academic fraud behavior

H7d: Misuse of AI-generated content mediates the relationship between rationalization and academic fraud behavior

RESEARCH METHOD

This study employs a quantitative research approach with a causal-explanatory design, aiming to investigate the influence of fraud diamond factors on academic fraud, mediated by misuse of AI-generated content and moderated by Machiavellianism. The analytical framework is grounded in structural equation modeling using the SEM-PLS (Structural Equation Modeling - Partial Least Squares) technique, which is suitable for predictive and exploratory research involving complex models and latent constructs (Hair et al., 2021).

The target population comprises students majoring in Financial Accounting program at Politeknik Negeri Sambas, with a total of 373 students. The sampling technique used was purposive sampling, targeting students who have taken or are currently taking the Professional and Business Ethics course. The sample size was initially determined using the Slovin formula with a 5% margin of error, resulting in a minimum sample requirement of 193 respondents. However, the study successfully collected valid responses from 243 students, which enhances the statistical power and generalizability of the findings. The sample was obtained using proportionate stratified random sampling, ensuring fair representation across academic levels.

Primary data were collected through a structured online questionnaire using Google Forms, which was distributed via class WhatsApp groups. The questionnaire utilized 4-point Likert scales ranging from 1 (*strongly disagree*) to 4 (*strongly agree*) to measure constructs (refer to table 1).

The collected data were analyzed using SmartPLS version 4, applying the Partial Least Squares Structural Equation Modeling (SEM-PLS) method. SEM-PLS was chosen due to its ability to: 1) Handle complex models with mediators and moderators; 2) Accommodate non-normal data distributions; 3) Perform predictive-oriented analysis.

The analysis was conducted in two stages: Measurement Model Evaluation (Outer Model) and Structural Model Evaluation (Inner Model). Model fit was assessed using the Standardized Root Mean Square Residual (SRMR) and other fit indices such as d_ULS, d_G, Chi-square, and NFI. The outer model evaluation assessed indicator reliability, convergent validity through Average Variance Extracted (AVE) and outer loadings, and discriminant validity using cross loadings. The structural model evaluation examined path coefficients to test the direct, mediating, and moderating effects among variables.

RESULT AND DISCUSSION

The respondents in this study were students enrolled in the Financial Accounting program at Politeknik Negeri Sambas. A total of 243 completed questionnaires were collected and deemed valid for analysis.

Evaluation of the Outer Measurement Model

The evaluation of the outer measurement model was conducted to assess the convergent validity, internal reliability, and discriminant validity of the constructs used in this study. Based on the SmartPLS 4 analysis results, all constructs met the fundamental criteria for measurement quality within the SEM-PLS framework (refer to table 2).

In general, the factor loadings for most indicators exceeded the recommended threshold of 0.70, indicating a strong contribution of the indicators to their respective constructs. However, a few indicators exhibited loadings between 0.40 and 0.70, such as AF1 (0.496), AI1 (0.698), C1 (0.447), O4 (0.624), and O5 (0.691). Following the guideline by (Hair et al., 2021) , indicators within this range are acceptable if the Average Variance Extracted (AVE) of the associated construct meets the minimum threshold of 0.50. In this study, all constructs demonstrated AVE values ranging from 0.560 to 0.676, satisfying the criterion for convergent validity. Therefore, all indicators were retained for further analysis.

Regarding Composite Reliability (CR), all constructs achieved values above the recommended 0.70 threshold, with CR scores ranging from 0.883 to 0.912. This result indicates a high level of internal consistency for all constructs. Similarly, the Cronbach's Alpha values were above 0.80 across all constructs, providing additional evidence for satisfactory internal reliability.

For convergent validity, the AVE values of all constructs exceeded the required 0.50 benchmark, ensuring that more than 50% of the variance in the indicators was captured by their respective latent variables. This confirms that the constructs possess strong convergent validity.

The cross loading analysis in the measurement model demonstrates acceptable discriminant validity, as each indicator loads highest on its intended construct compared to other constructs (refer to table 3). Similarly, Capability (C), Opportunity (O), Pressure (P), Rationalization (R), and Machiavellianism (MAC) each show consistent patterns where their indicators have the strongest associations with their respective latent variables. This suggests that the items are conceptually and statistically distinct, supporting the reliability of the measurement model. The interaction term (MAC × AI) also behaves as expected, with a perfect loading on itself (1.000) and weak correlations with other constructs, affirming its role as a moderating variable. Overall, the cross loading results confirm that the model possesses good discriminant validity.

Overall, the results of the outer measurement outer model evaluation suggest that the constructs in this study demonstrate acceptable levels of reliability and validity. Consequently, the model is considered appropriate for further examination in the structural model analysis phase. Thus, the proposed model testing the influence of Fraud Diamond elements on Academic Fraud Behavior, mediated by Misuse of AI-Generated Content and moderated by Machiavellianism, can proceed with confidence in the robustness of its measurement properties.

Evaluation of Model Fit

The model fit evaluation using SmartPLS 4 indicated an acceptable overall model fit (refer to table 4). The SRMR values for both the saturated (0.070) and estimated models (0.071) were below the recommended threshold of 0.08, signifying a good fit. Although no strict cut-offs exist for d_ULS and d_G, the values were reasonably low and comparable between models, suggesting a good approximation. The

Chi-square values were high, as expected with larger samples, but are used descriptively in PLS-SEM. The NFI values, at 0.735 (saturated) and 0.734 (estimated), exceeded the 0.70 benchmark for exploratory research. Overall, the results confirm that the model adequately fits the data.

Evaluation of Inner Model

The evaluation of the structural model was performed by examining the path coefficients, significance levels (p-values), and effect sizes (refer to table 5). The hypothesis testing results reveal important insights regarding the relationships among the variables proposed in the research model.

Starting with Hypothesis H1a, the findings show that pressure has a significant positive effect on misuse of AI-generated content ($\beta = 0.158$, $p = 0.019$, $f^2 = 0.023$), thus supporting H1a. This suggests that students experiencing higher levels of academic pressure are more likely to misuse AI technologies in their academic tasks. Similarly, Hypothesis H1b is also supported, with pressure significantly influencing academic fraud behavior ($\beta = 0.099$, $p = 0.033$, $f^2 = 0.011$). These results align with fraud theories, which argue that external pressure can directly drive individuals toward unethical behavior.

Regarding Hypothesis H2a, the relationship between opportunity and misuse of AI-generated content was found to be insignificant ($\beta = 0.001$, $p = 0.498$, $f^2 = 0.000$), leading to the rejection of H2a. This indicates that the presence of opportunity alone does not necessarily prompt students to misuse AI tools. However, Hypothesis H2b was supported, as opportunity has a significant positive effect on academic fraud behavior ($\beta = 0.151$, $p = 0.036$, $f^2 = 0.018$), implying that when opportunities arise, students may directly engage in fraudulent actions.

For Hypothesis H3a, capability was shown to have a strong and significant positive influence on misuse of AI-generated content ($\beta = 0.330$, $p = 0.000$, $f^2 = 0.060$), thus supporting H3a. This finding highlights that students with higher technological skills are more adept at exploiting AI tools for academic misconduct. Additionally, Hypothesis H3b was accepted, showing that capability significantly impacts academic fraud behavior ($\beta = 0.196$, $p = 0.022$, $f^2 = 0.023$), indicating that technical competence not only increases AI misuse but also contributes directly to unethical academic practices.

Moving to Hypothesis H4a, rationalization was found to significantly affect misuse of AI-generated content (β = 0.237, p = 0.015, f^2 = 0.027), thereby supporting H4a. This result suggests that when students are able to justify unethical behavior, they are more inclined to misuse AI tools. In contrast, Hypothesis H4b was rejected because the direct effect of rationalization on academic fraud behavior was insignificant (β = 0.006, p = 0.470, f^2 = 0.000). This finding implies that rationalization alone may not directly lead to fraudulent behavior unless mediated by other factors.

Hypothesis H5, which proposed a direct positive effect of misuse of AI-generated content on academic fraud behavior, was not supported (β = 0.111, p = 0.062, f^2 = 0.015). Although AI misuse is prevalent, it may not directly result in academic fraud without being influenced by other mediating or moderating variables. Lastly, Hypothesis H6, which tested the moderating role of Machiavellianism on the relationship between AI misuse and academic fraud behavior, was also rejected (β = -0.075, p = 0.132, f^2 = 0.012). This indicates that Machiavellian traits do not significantly strengthen or weaken the impact of AI misuse on fraudulent academic behavior.

Moving to the mediation hypotheses, Hypothesis H7a proposed that misuse of AI-generated content mediates the relationship between pressure and academic fraud behavior. The analysis yielded a statistically significant indirect effect (β = 0.018, p =0.108, f^2 = 0.023); H7a is rejected. This suggests that while students under academic pressure may be more inclined to misuse AI tools, this misuse does not significantly translate into academic fraud.

For Hypothesis H7b, which examined the mediating role of AI misuse between opportunity and academic fraud behavior, the results showed an insignificant indirect effect (β = 0.000, p = 0.498, f^2 = 0.000), leading to the rejection of H7b. This indicates that the availability of opportunity alone is not sufficient to drive misuse of AI, nor does it indirectly influence academic dishonesty through such misuse.

Hypothesis H7c tested whether capability influences academic fraud behavior through the misuse of AI-generated content. The results showed a statistically significant indirect effect (β = 0.037, p = 0.086, f^2 = 0.060), H7c is also rejected. This suggests that while capable students are more adept at utilizing AI, their misuse of such tools does not strongly mediate the pathway to academic fraud.

Finally, Hypothesis H7d assessed the mediating effect of AI misuse in the relationship between rationalization and academic fraud. Although the indirect effect was statistically significant (β = 0.026, p = 0.116, f^2 = 0.027), H7d is rejected. This implies that rationalizing unethical behavior may be linked to AI misuse, but such misuse does not effectively bridge the rationalization–fraud behavior relationship.

Discussion

The results support Hypothesis 1a, indicating that academic pressure significantly influences the misuse of AI-generated content. This aligns with studies showing that students under intense academic pressure are more likely to misuse AI tools like ChatGPT to cope with heavy workloads and deadlines (Alamanda et al., 2024; Alshurafat et al., 2024). ducational institutions need to manage the academic pressure experienced by students—for instance, by adjusting workloads, extending deadlines, or providing counseling services. Reducing pressure may decrease students' tendencies to use AI unethically as a form of escape. Similarly, Hypothesis 1b is supported, as pressure also directly increases academic fraud behavior. These findings reinforce the Fraud Diamond Theory, which highlights pressure as a primary motivator for fraudulent actions (Anggraini et al., 2024; Miranda et al., 2023). Thus, preventive approaches are required, including more supportive learning strategies and assessments that focus not only on performance but also on the learning process.

Hypothesis 2a is rejected, indicating that opportunity does not significantly affect the misuse of AI-generated content. This finding is consistent with previous research suggesting that merely having the opportunity—such as weak supervision or easy access to AI tools—is not sufficient to encourage misuse among students, as individual factors like personal ethics, academic integrity, and self-control play a more decisive role in their decision-making (Johnston et al., 2024; Kapoor et al., 2025). This implies that efforts to prevent AI misuse in academic settings should not solely focus on limiting access or increasing surveillance, but also on enhancing ethical awareness, motivation, and students' sense of responsibility. However, Hypothesis 2b is accepted, showing that opportunity has a significant direct effect on academic fraud behavior. These results indicate that while opportunity creates conditions conducive to academic dishonesty, additional factors are needed to mediate the use of AI tools. Previous research also supports the notion that opportunity increases the likelihood of fraud, but this must interact with personal motivation or capabilities to translate into AI misuse (Kusumayanti & Utama, 2024; Neva & Amyar, 2021). The presence of opportunity—such as weak supervision or ineffective fraud detection systems—encourages dishonest behavior. Therefore, institutions should strengthen exam and assessment monitoring systems and enhance reporting mechanisms for academic integrity violations.

The data supports Hypothesis 3a, indicating that capability positively influences the misuse of AI-generated content. This highlights that students with better technical skills and AI understanding are more proficient in using these tools unethically (Chan & Tsi, 2023; Mohammadkarimi, 2023). Technically skilled students are at greater risk of AI misuse. Thus, digital literacy training should be integrated with ethical use components so that competence does not correlate directly with potential misuse. Hypothesis 3b is also supported, indicating a direct positive effect of capability on academic fraud behavior. This finding strengthens the notion that technical competence facilitates dishonest acts by enabling students to exploit AI while avoiding detection (Alamanda et al., 2024; Rachmawati et al., 2024). High technical capability can serve as a sophisticated tool for academic dishonesty. Therefore, it is essential to monitor the use of digital tools in academic processes and emphasize moral responsibility as a core 21st-century skill.

Hypothesis 4a is supported, as rationalization significantly affects the misuse of AI-generated content. Students often justify their misuse of AI by downplaying its unethical nature or normalizing it due to peer influence (Alshurafat et al., 2024; Savitri, 2025). Students who are able to rationalize their actions are more likely to misuse AI. Hence, explicit instruction on the ethical consequences of academic misconduct and case-based learning should be implemented to sharpen students' moral judgment. However, Hypothesis 4b is rejected, suggesting that rationalization alone does not directly predict academic fraud behavior. This may imply that rationalization primarily affects dishonest conduct by enabling AI misuse, rather than directly driving fraudulent acts. Prior studies have also emphasized that rationalization plays a role in shaping attitudes that allow fraud to occur, rather than serving as a direct trigger of behavior (Anggraini et al., 2024; Juliardi et al., 2021; Muhsin et al., 2017). Since rationalization does not directly drive fraud, institutions should focus on preventing its development—

through discussions on academic values and integrity culture—rather than only addressing the outcomes of dishonest behavior.

The direct influence of AI content misuse on academic fraud behavior is not supported, indicating that AI misuse alone may not be sufficient to cause fraud, or that other mediating factors may play a larger role. This finding suggests the complexity of academic fraud behavior in digital contexts, where AI misuse is just one of many possible pathways (Harahap, 2024; Rahardyan et al., 2024) . AI misuse does not necessarily lead directly to fraud, meaning that technology is merely a tool. Therefore, strong academic integrity values must be instilled so that even with access and capability, students choose ethical paths.

The moderating effect of Machiavellianism on the relationship between AI content misuse and academic fraud behavior is rejected. This indicates that, contrary to expectations, Machiavellian traits do not significantly strengthen the relationship between AI misuse and academic dishonesty in this sample. Although Machiavellianism is associated with manipulativeness and unethical tendencies (Basri et al., 2023) , its moderating role may differ depending on contextual or cultural factors, or it may operate through different mechanisms than AI misuse. Further research using qualitative approaches may be needed to explore this dynamic more deeply.

All mediation hypotheses (H7a to H7d) are rejected, indicating that AI-generated content misuse does not mediate the relationships between pressure, opportunity, capability, or rationalization and academic fraud behavior. Although the dimensions of the Fraud Diamond have significant direct effects on academic fraud, the indirect pathways through AI misuse are not significant. This finding contradicts some previous studies suggesting that technology misuse is a key mediator (Alshurafat et al., 2024; Herawaty & Masbirorotni, 2022) . It suggests that the primary causes of fraud remain rooted in psychological and situational factors, not merely in technology misuse. Interventions should focus on character building, ethical reinforcement, and comprehensive academic control systems.

CONCLUSION

This study concludes that the elements of the Fraud Diamond Theory—pressure, opportunity, capability, and rationalization—play important roles in explaining academic fraud behavior, particularly in the context of emerging AI technologies. The results show that pressure and capability significantly contribute to both the misuse of AI-generated content and academic fraud, while rationalization influences AI misuse but not fraud directly. Opportunity significantly predicts academic fraud but not AI misuse. Although misuse of AI-generated content was hypothesized to mediate the relationship between these factors and academic fraud, its effect was found to be limited. Furthermore, the moderating role of Machiavellianism in strengthening the relationship between AI misuse and academic fraud behavior was not supported. These findings offer a more nuanced understanding of how psychological and technological factors interact with contextual variables to shape unethical academic conduct. To strengthen students' ethical awareness in the digital age, educational institutions should integrate ethical training into the curriculum, particularly on the responsible use of AI tools. Emphasizing that AI is not an enemy but a neutral instrument—whose impact depends on how it is used—can help students view technology as a tool to support learning, not a shortcut to bypass academic responsibilities. Furthermore, fostering a culture of academic integrity, promoting discussions about real-world ethical dilemmas, and implementing clear policies regarding AI use can equip students with both the technical competence and moral discernment needed to navigate an AI-enhanced academic environment responsibly.

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TABLES AND FIGURES

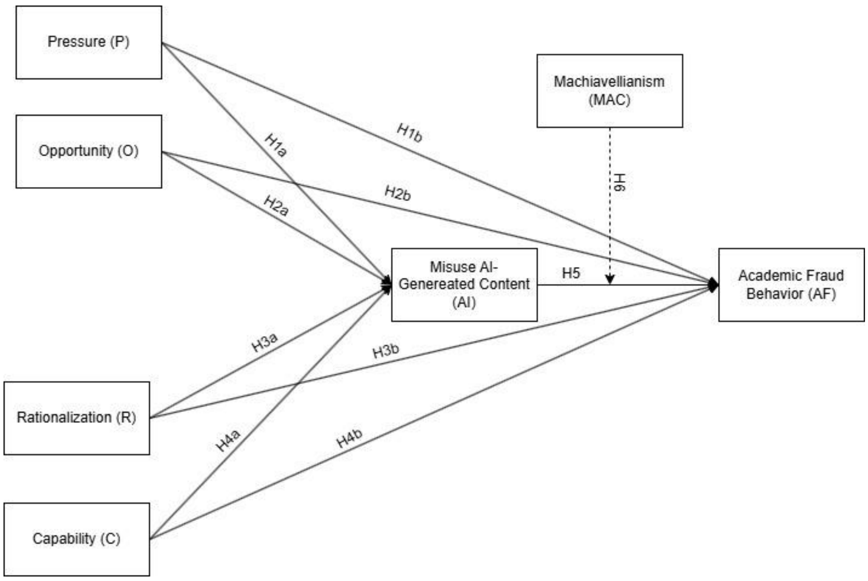

Figure 1. Research Design

Table 1. Research Instrument

Variable	Instrument
Pressure	I must pass the exam, even if I committed plagiarism in my assignment.
	I must pass the exam, even though I cheated.
	I cheated during the exam to get the highest grade.
	I committed academic dishonesty together with others to pass the exam with a high score.
	I committed plagiarism in my assignment due to a lack of time
Opportunity	The lecturer does not carefully check students' assignments, so I committed plagiarism/cheated
	Cheating is not a problem as long as you don't get caught.
	The exam proctor allows students to cheat.
	The lecturer does not check assignments using plagiarism detection software (e.g., Turnitin).
	I am not afraid to cheat during exams.
	I cheated because the exam proctor was preoccupied with other activities instead of monitoring.
Rationalization	I believe cheating can be justified when I am under extreme pressure, such as having limited time.
	I feel that I am not harming anyone when I cheat during an exam.
	If I get caught cheating, the consequences are not too severe.
	Cheating or committing academic dishonesty is common among me and my peers.
	I think cheating is acceptable if many others are doing it too.
Capability	I do not feel afraid or anxious when I cheat.
	I make plans or strategies to enable me to cheat during exams.
	I can provide excuses if I am accused of committing academic dishonesty.
	I ask my friends to help me cheat.
	I can manipulate my surroundings to support my cheating.
Misuse Of Ai-Generated Content	I use AI-based tools, such as ChatGPT or others, to generate part or all of my assignment content without disclosing that it was created by AI.
	I submit assignments that are entirely generated by AI tools without reviewing their accuracy or context.
	I complete assignments solely using AI-based tools without attempting to

	understand the process manually.
	I use chatbots or other AI-based tools to find answers during exams (take-home or online) that are supposed to be completed independently.
	I use AI-based tools to create fake research data that is not based on actual observations or experiments.
Machiavellianism	I might sabotage others' efforts if they threaten my goals.
	I believe that cheating during exams can be justified if it leads to a positive outcome.
	I try to take the lead in group decisions, including cheating strategies when necessary.
	I cheat or commit plagiarism to achieve high grades so I can be perceived as smart.
	I engage in academic dishonesty to gain recognition from peers, lecturers, or my parents.
Academic Fraud Behavior	I did not cite sources in my essay/paper assignments.
	I simply copied a friend's assignment.
	I created/prepared cheat sheets for an exam.
	I used cheat sheets during an exam.
	I copied a friend's answers during an exam.
	I collaborated with friends to cheat during an exam.

Tabel 2. Factor loading, AVE, reliability, and R square

Variables	Factor Loading	AVE	Composite Reliabiity	Chronchbach alpha	R Square
AF1	0.496	0.617	0.904	0.868	0,561
AF2	0.789				
AF3	0.856				
AF4	0.858				
AF5	0.824				
AF6	0.827				
AI1	0.698				
AI2	0.795				
AI3	0.801				0,442
AI4	0.811				
AI5	0.802	0.612	0.887	0.842	
C1	0.447	0.610	0.900	0.863	
C2	0.828				
C3	0.851				
C4	0.728				
C5	0.862				
C6	0.881				
MAC1	0.778	0.676	0.912	0.879	
MAC2	0.824				
MAC3	0.770				
MAC4	0.889				
MAC5	0.844				
O1	0.765	0.560	0.883	0.841	
O2	0.807				
O3	0.757				
O4	0.624				
O5	0.691				
O6	0.828				
P1	0.820	0.613	0.904	0.871	
P2	0.854				
P3	0.806				

P4	0.818				
P5	0.738				
P6	0.643				
R1	0.841				
R2	0.803				
R3	0.760	0.667	0.909	0.875	
R4	0.835				
R5	0.843				
MAC x AI	1.000				

Table 3. Cross Loadings

	AF	AI	C	MAC	O	P	R	MAC x AI
AF1	0.496	0.480	0.402	0.339	0.446	0.353	0.427	-0.040
AF2	0.789	0.455	0.553	0.546	0.462	0.443	0.475	-0.032
AF3	0.856	0.454	0.498	0.588	0.476	0.444	0.482	0.030
AF4	0.858	0.469	0.531	0.623	0.460	0.438	0.469	0.074
AF5	0.824	0.383	0.616	0.562	0.531	0.459	0.498	-0.026
AF6	0.827	0.476	0.610	0.537	0.597	0.511	0.601	-0.037
AI1	0.315	0.698	0.385	0.383	0.384	0.362	0.435	-0.138
AI2	0.424	0.795	0.434	0.463	0.372	0.370	0.387	-0.037
AI3	0.441	0.801	0.473	0.498	0.298	0.354	0.409	-0.068
AI4	0.449	0.811	0.472	0.441	0.490	0.437	0.524	-0.058
AI5	0.565	0.802	0.613	0.650	0.503	0.500	0.574	0.117
C1	0.231	0.354	0.447	0.305	0.407	0.281	0.386	-0.134
C2	0.570	0.521	0.828	0.668	0.601	0.546	0.691	0.038
C3	0.609	0.495	0.851	0.637	0.597	0.505	0.641	0.033
C4	0.461	0.459	0.728	0.542	0.514	0.448	0.596	-0.044
C5	0.643	0.514	0.862	0.662	0.665	0.566	0.681	0.040
C6	0.604	0.547	0.881	0.675	0.677	0.579	0.688	0.049
MAC1	0.516	0.473	0.575	0.778	0.468	0.400	0.511	0.222
MAC2	0.589	0.579	0.623	0.824	0.586	0.548	0.610	0.199
MAC3	0.516	0.487	0.604	0.770	0.567	0.440	0.546	0.076
MAC4	0.617	0.533	0.671	0.889	0.543	0.552	0.583	0.177
MAC5	0.579	0.540	0.659	0.844	0.543	0.500	0.582	0.131
O1	0.459	0.439	0.580	0.551	0.765	0.583	0.631	0.117
O2	0.501	0.366	0.600	0.468	0.807	0.530	0.646	0.033
O3	0.417	0.304	0.523	0.427	0.757	0.381	0.562	0.069
O4	0.403	0.374	0.396	0.374	0.624	0.301	0.432	-0.117
O5	0.426	0.426	0.522	0.485	0.691	0.427	0.518	-0.076
O6	0.601	0.454	0.690	0.609	0.828	0.568	0.673	-0.003
P1	0.365	0.413	0.436	0.468	0.468	0.820	0.484	0.138
P2	0.497	0.489	0.549	0.515	0.586	0.854	0.608	0.060
P3	0.431	0.342	0.518	0.459	0.462	0.806	0.527	0.063
P4	0.517	0.384	0.600	0.526	0.576	0.818	0.600	0.085
P5	0.403	0.447	0.454	0.386	0.484	0.738	0.503	-0.064
P6	0.421	0.373	0.414	0.437	0.359	0.643	0.344	0.127

R1	0.490	0.517	0.632	0.563	0.625	0.583	0.841	0.068
R2	0.511	0.467	0.606	0.540	0.633	0.545	0.803	-0.031
R3	0.559	0.495	0.671	0.559	0.600	0.541	0.760	-0.045
R4	0.507	0.492	0.676	0.587	0.633	0.512	0.835	0.085
R5	0.500	0.494	0.663	0.565	0.686	0.510	0.843	0.069
MAC x AI	-0.005	-0.031	0.013	0.197	0.006	0.085	0.035	1.000

Table 4. Model Fit Evaluation

	Saturated model	Estimated model
SRMR	0.070	0.071
d_ULS	3.775	3.906
d_G	1.453	1.475
Chi-square	1.887.295	1.898.566
NFI	0.735	0.734

Tabel 5. Hypothesis testing results

Hypothesis	Original sample (O)	P values	Effect Size	Decision
P -> AI	0.158	0.019	0.023	Accepted
P -> AF	0.099	0.033	0.011	Accepted
O -> AI	0.001	0.498	0.000	rejected
O -> AF	0.151	0.036	0.018	Accepted
C -> AI	0.330	0.000	0.060	Accepted
C -> AF	0.196	0.022	0.023	Accepted
R -> AI	0.237	0.015	0.027	Accepted
R -> AF	0.006	0.470	0.000	rejected
AI -> AF	0.111	0.062	0.015	rejected
MAC x AI -> AF	-0.075	0.132	0.012	rejected
P -> AI -> AF	0.018	0.108	0,023	rejected
O -> AI -> AF	0.000	0.498	0,000	rejected
C -> AI -> AF	0.037	0.086	0,060	rejected
R -> AI -> AF	0.026	0.116	0,027	rejected

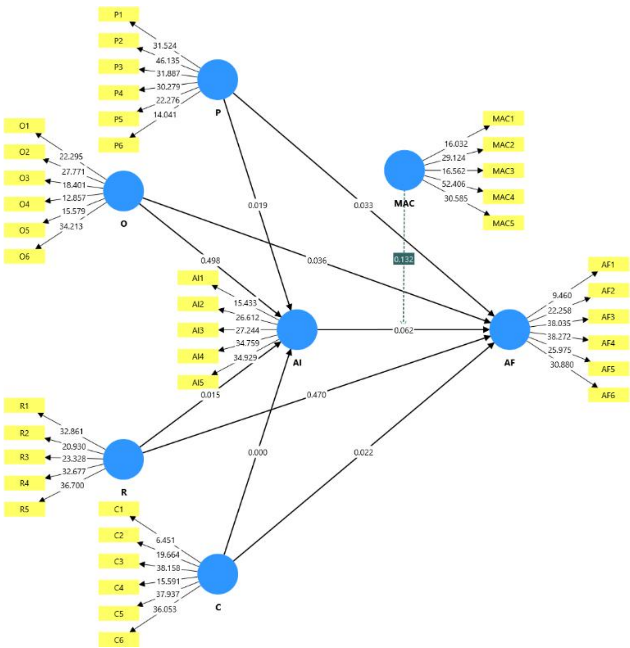

Figure 2. Main Structural Model Result