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EXAMINING THE DETERMINANTS OF AI MISUSE AMONG STUDENTS IN INDONESIA: AN ANALYSIS THROUGH THE FRAUD DIAMOND FRAMEWORK

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Abstract

The growing integration of artificial intelligence (AI) in academia raises ethical concerns, particularly among business and accounting students expected to uphold professional integrity. This study examines factors influencing the use of AI for academic misconduct among Indonesian business students, applying the Fraud Diamond Theory as a framework. An online survey conducted from August 2024 to January 2025 yielded 424 valid responses, analyzed using SmartPLS version 4.1.0.9. The findings reveal that students do not view opportunity as a significant determinant of AI-assisted misconduct. Instead, capability, rationalization, and motivation significantly affect students' intentions to engage in such behavior. This study contributes to literature and practice by highlighting ethical challenges in AI adoption within education, especially in Indonesia. It emphasizes the need for ethical AI training, enhanced digital literacy, and clear institutional protocols to address ethical dilemmas. Understanding the key drivers of AI-assisted misconduct supports the development of effective prevention and detection strategies. Given its focus on Indonesian business and accounting students, the study calls for broader validation with diverse samples and objective measures. Future research should explore the long-term impact of AI use on professional ethics, educational integrity, and intervention effectiveness.

Keywords: *Academic cheating; Artificial intelligence; Business and accounting students; Diamond fraud theory.*

Abstrak

Peningkatan integrasi kecerdasan buatan dalam dunia akademik menimbulkan kekhawatiran etis, khususnya di kalangan mahasiswa bisnis dan akuntansi yang diharapkan menjunjung tinggi integritas profesional. Penelitian ini mengkaji faktor-faktor yang memengaruhi penggunaan AI untuk melakukan kecurangan akademik di kalangan mahasiswa bisnis di Indonesia, dengan menggunakan *Fraud Diamond Theory* sebagai kerangka konseptual. Survei daring yang dilakukan sejak Agustus 2024 hingga Januari 2025 menghasilkan 424 tanggapan valid yang dianalisis menggunakan SmartPLS versi 4.1.0.9. Hasil penelitian menunjukkan bahwa mahasiswa tidak memandang faktor peluang sebagai penentu dalam melakukan kecurangan akademik berbantuan AI. Sebaliknya, faktor kapabilitas, rasionalisasi, dan motivasi berpengaruh signifikan terhadap niat mahasiswa untuk melakukan tindakan tersebut. Penelitian ini memberikan kontribusi bagi literatur dan praktik dengan menyoroti tantangan etika dalam adopsi AI di lingkungan pendidikan di Indonesia. Studi ini menekankan pentingnya pelatihan etika dalam penggunaan AI, peningkatan literasi digital, serta penerapan protokol institusional yang jelas dalam menghadapi dilema etis. Pemahaman terhadap faktor-faktor utama kecurangan akademik berbantuan AI mendukung pengembangan strategi pencegahan dan deteksi yang efektif. Mengingat fokus penelitian pada mahasiswa bisnis dan akuntansi di Indonesia, diperlukan validasi lebih luas dengan sampel beragam dan pengukuran yang lebih objektif. Penelitian selanjutnya diharapkan dapat mengeksplorasi dampak jangka panjang penggunaan AI terhadap etika profesional, integritas akademik, dan efektivitas intervensi.

Kata Kunci: Kecerdasan buatan; Kecurangan akademis; Mahasiswa bisnis dan akuntansi; Teori fraud diamond.

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INTRODUCTION

The rapid rise of AI has brought new challenges to academic integrity. Its widespread use has created more opportunities for dishonesty and added pressure on students (Almasri, 2024). The line between acceptable research and academic dishonesty is blurred now more than ever. Survey findings indicate that many undergraduate students may utilize AI systems, including ChatGPT, to complete pseudo-projects and tests, raising questions about ethical behavior and the value of education (BestColleges, 2023). This phenomenon raises a serious concern about the sheer ease with which AI systems could produce academic writing, thus threatening originality and academic integrity.

Academic dishonesty entails all sorts of acts that disrupt the fairness and integrity of the educational system (Smith et al., 2023; Tauginienė et al., 2018). It may occur in various ways, such as referencing sources, cheating on exams, falsifying research, or simply plagiarizing. It also creates an uneven playing ground in academia and has ramifications on the broader society. As earlier studies have noted, there is a risky connection between academic dishonesty at the higher educational level and unethical practices in the work environment, which could damage businesses and society (Mulisa & Ebessa, 2021).

Particularly among business students, there appears to be a higher tendency towards academic dishonesty than their peers in other fields (Mccabe & Butterfield, 2006; Parks-Leduc et al., 2022). Encouraging factors include favorable attitudes toward cheating, supportive social norms, and a sense of freedom to cheat (Ababneh et al., 2022). In some ways, Joining competitive programs can encourage unethical behavior, as the pressure to excel and meet high standards of originality and innovation often leads stressed students to engage in academic dishonesty (Ferguson et al., 2022; Hughes & Eaton, 2022).

Business schools also have specific standardized systems of grading, which tend to encourage cheating from the student's point of view, for they want to gain an edge over their fellow students (Sharma et al., 2024).

Meanwhile, accounting students are exposed to business ethics and anti-corruption law courses, which examine in-depth ethical conduct. The IAESB (2019) even integrate ethics into the learning outcomes of accounting degree as accounting students are expected to be future anti-fraud professionals in the industry. Consequently, it is concerning that students are misusing AI to enable them to cheat during their studies. Such practice could cause misleading financial reporting and sets graduates who cannot apply their knowledge in a real-world context (Smith et al., 2021). Universities should, therefore, put in place a policy framework designed to mitigate AI-assisted cheating.

Despite growing attention to academic dishonesty and technology, existing research provides limited understanding of how AI, in general, is used for cheating. A major weakness in prior studies is their narrow focus on a single AI tool, such as ChatGPT (Alshurafat et al., 2024; Ofem et al., 2024; Sallam et al., 2023), which restricts the generalizability of their findings to other AI applications that may facilitate dishonest behavior. Furthermore, because AI technologies evolve rapidly, studies centered on specific tools risk becoming quickly outdated (Sharma et al., 2024). This indicates a clear gap in research exploring the misuse of diverse and emerging AI systems in academic contexts.

Another significant limitation lies in the geographical and contextual scope of prior research. In Indonesia, for instance, studies on online academic dishonesty remain scarce, and even fewer examine the role of AI among Indonesian students. Ampuni et al. (2020) investigated academic dishonesty without considering AI involvement, while other studies have focused mainly on factors influencing online cheating (Sholikhah et al., 2024) or on AI detection tools rather than AI as a facilitator of misconduct (Yulita et al., 2023). Consequently, little is known about how Indonesian business and accounting students perceive and use AI in dishonest ways—an understanding essential for developing culturally sensitive and contextually relevant preventive measures.

Theoretical limitations also characterize much of the existing literature. Most studies on academic dishonesty rely on the Fraud Triangle Theory, with limited application of the more comprehensive Fraud Diamond framework. Although Smith et al. (2023) employed the Fraud Diamond to analyze online cheating, they did not specifically address how AI can enhance students' capacity to engage in dishonest practices. Similarly, studies by Alshurafat et al. (2024), Bierstaker et al. (2024), Bujaki et al. (2019), and Sharma et al. (2024) focus predominantly on traditional motivators of cheating while neglecting the crucial "capability" dimension an aspect particularly relevant when examining how students exploit AI technologies.

Capability is one of Fraud Diamond's key concepts that is vitally essential in understanding acts of fraud, specifically when it comes to academic misconduct aided by AI. Capability reflects the skills, resources, and accesses individuals can use to exploit vulnerabilities and, as this research suggests, undergirding the effect of pressure, opportunity, and rationalization in bringing a fraudulent act to fruition (Avortri & Agbanyo, 2021; Firdaus et al., 2022; Vousinas, 2019; Wolfe & Hermanson, 2004). The research models that apply the fraud triangle theory may be insufficient to predict dishonest students' intention to cheat using AI if they do not incorporate the students' capability to use AI tools. AI-assisted academic misconduct must be viewed considering the Fraud Diamond theory for a better understanding, which will provide further insight into what is fueling this emerging menace. Thus, applying the Fraud Diamond theory, this research aims to examine the factors influencing business accounting students' misuse of AI software in academic dishonesty.

This research contributes to both academic and practice. It broadens the literature on fraud diamond theory in studying AI misuse determinants relative to business and accounting students. While other studies have examined either generalized academic misconduct or countermeasures, this one concentrates on the malevolent intentions and capabilities behind AI-assisted cheating involving Indonesian business students, providing valuable case studies for developing nations facing similar issues through the Indonesian viewport.

As a reality, the study acts as a reminder that there is a necessity to train the students on how they will apply AI ethically, academic integrity, digital literacy skills, and ethical decision-making. The universities should also provide clear standards of ethics along with the use of AI in an ethical way and also take their students through ethical dilemmas. Understanding the reason behind AI cheating among students (their abilities, justification, and incentives) helps make institutions devise effective AI cheating detection and prevention measures. The initiative helps to develop responsible application of technology and cultivate student helping and critical thinking.

LITERATURE REVIEW

Motivation and Intention to Misuse Artificial Intelligence

Fraud diamond theory is the powerful model in explaining intricate complexity in committing an act of fraud. It highlights the interaction of four key aspects that include rationalization, opportunity, pressure and capability (Wolfe & Hermanson, 2004). This notion has gained much prominence of late with researchers examining how it applies to most scenarios including financial statement fraud and academic dishonesty.

The motivational component of the fraud diamond theory can also have an explanation according to which in case a person really feels pushed either by external circumstances or inner compulsions, the readiness to do something wrong is more than likely to be defeated. Reasons such pressure may be due to their own financial demands, or unjust enrichment or due to being placed under the extreme pressure to reach unrealistic objectives.

These pressures can have negative and positive consequences (Omukaga, 2020). It can assist one to do the right thing when temptation seems overwhelming and can be a force for good if the pressure to achieve a goal is intense enough within reasonable limits. However, when pressure is excessive, it can bring about serious consequences, such as fraudulent behavior. The pressures can arise due to several issues, such as financial needs (Arkorful et al., 2022), performance expectations (Fransiska & Utami, 2019; Kazemian et al., 2019; Khamainy et al., 2022), personal circumstances (Said et al., 2017, 2018), and so on.

The recent study has continuously emphasized the financial necessity as the powerful sources of pressure on fraudulent intentions. They insisted that one among the significant pressure points is financial needs (Arkorful et al., 2022). Their argument would imply that once individuals are forced to live under the pressures of increasing debts or sudden financial difficulties, sudden economic distress, or simply being placed under such a situation, chances are strong that persons would be able to calculate and exploit a position of benefit to themselves. Avortri and Agbanyo (2021) confirm that pressure gives rise to baseline situations, which enable the personal financial needs to have control on the occurrence of fraud.

Beyond financial strain, organizational factors and performance expectations, can also serve as forms of pressure. Khamainy et al. (2022) suggest that pressure arising from factors such as meeting unrealistic performance targets, upholding a specific lifestyle, or impressing superiors tends to drive financial statement fraud. These pressures are consistent with the environment of employee fraud in the Malaysian banking industry, where pressures to meet financial targets were said to contribute to fraud (Said et al., 2017). Besides, pressure to conform to organizational culture can encourage individuals to engage in unethical behaviors needed to meet business objectives, even at the expense of their integrity, which lays heavy pressure again (Liang et al., 2022; Tepper, 2010).

The emergence of AI-assisted academic dishonesty adds a new layer to the existing pressures within academia (Alshurafat et al., 2024). The traditional fears of failure and competition remain relevant; however, the evolving landscape of digital tools adds even more pressure on dishonesty (Nguyen & Goto, 2024; Walker, 2010). Students, often unaware of their actions' unethical and illegal implications, may perceive AI as a solution to these pressures (Jones, 2011). This is particularly true for a high-achieving student who spends much time on a particular task and then feels troubled about meeting expectations in the environment and nervous about how this will affect their future career (Ababneh et al., 2022). In other words, students feel pressured to outperform their peers or secure prestigious job opportunities, leading them to rationalize AI-assisted cheating as a means to an end.

The ease with which AI can be used for academic dishonesty, coupled with the challenges in detection, further amplifies the pressure (Playfoot et al., 2024). In a competitive academic environment where success is paramount, the perception that peers are harnessing every advantage, including AI, for an unfair advantage further grinds students toward unethical behavior (McIntire et al., 2024; Sweeney, 2023). Therefore, it can be hypothesized that:

H$_1$: The presence of motivation significantly increases the students' cheating behavior using artificial intelligence tools.

Opportunity and Intention to Misuse Artificial Intelligence

The Fraud Diamond puts forward opportunity, along with motivation, capability and rationalization, as one of the major driving forces behind dishonest acts. An opportunity arises when individuals perceive they can commit and conceal dishonest acts without detection (Vousinas, 2019), often due to factors like weak corporate governance and controls and unethical leadership that create vulnerabilities for exploitation (Khamainy et al., 2022; Omukaga, 2020). Other circumstances in the digital era, such as online platforms and e-commerce open new for identity theft, credit card fraud, and other forms of cybercrime (Sharma et al., 2024). The internet is a wide-open medium; proving who the actors behind the crimes are becomes another challenge for law enforcement agencies trying to put these fraudsters behind bars (Jang-Jaccard & Nepal, 2014).

The academic world has not been left out concerning the influence of opportunity on dishonest behavior. By tradition, opportunities for academic misconduct may have included copying from a classmate during an exam or straightforwardly plagiarizing from easy-to-access physical resources. The message is simple: The digital age has ushered in opportunities for the application of new cheating methods (Zayed, 2023). For instance, while online courses can be flexible and accessible, they are often not beset by stringent proctoring methods, generating a perception among students that academic dishonesty may be permitted in this particular setting (Dendir & Maxwell, 2020). Such perceptions find support in ample online resources, from essay mills offering custom-written assignments to websites providing answers to homework questions (Nath & Lovaglia, 2009).

The advancements in recent AI tools such as ChatGPT have added immensely to the opportunities in this regard, marking a distinguishing line of support till cheating (Sharma et al., 2023). The availability of these tools, primarily for free or at a low cost, makes cheating that much easier (Alshurafat et al., 2024). As such, AI-generated text can pose a challenge to educators as students may try these tools for dishonest means, especially since current detection means have their limitations (Hosseini et al., 2023).

Several studies already recognize the link between opportunity and AI-assisted academic malfeasance. For instance, AI is being used by students to pass university examinations, assess research material, give feedback, obtain and analyze data, and track information that may have been traditionally unavailable (Choi et al., 2022; Tareq et al., 2023). Opportunity did play its role as online course cheating dropped noticeably once proctoring measures were instituted (Dendir & Maxwell, 2020). Similar treatments of plagiarism show that students are more likely to plagiarize from cheap online sources than printed materials (Playfoot et al., 2024). This confers credence to the assertion that the risk environment created by readily available resources encourages unethical academic behaviour. Therefore, it can be hypothesized that:

H_2: The presence of opportunity significantly increases students' cheating behavior using artificial intelligence tools.

Rationalization and Intention to Misuse Artificial Intelligence

Rationalization is a critical element of the fraud triangle: it is the cognitive process through which individuals justify their unethical acts. Self-deception allows perpetrators to align their behavior with their self-image as ethical persons, which mitigates the resulting cognitive dissonance and enables them to retain their sense of integrity, having acted in an unethical manner (Ramamoorti, 2008). Rationalization may appear as a morally acceptable excuses in perpetrator reasoning that banish the appraisal of the act as a criminal from one's mind. Common rationalizations include minimizing the harm caused, shifting blame to the victim or circumstances, appealing to higher loyalties, or viewing the act as a necessary evil (Avortri & Agbanyo, 2021). The rationalization reduces the internal pressure of morality, thereby making possible the unethical act of the person in the first place and creating pathways for repeated wrongdoing in the future (Ratmono & Frendy, 2022).

This process of rationalization, which is serving as an early warning signal to confront and overcome any cheating guilt, has also been the subject of other behavioral studies (Trompeter et al., 2013). articulated eight kinds of denials, including denial of legality, responsibility, injury, and victim, along with forms of social weighting, appeal to higher loyalties, the metaphor of the ledger, and refocusing attention. Some scholars have linked this rationalization process with techniques of neutralizing guilt before engaging in fraud. In so doing, individuals perceive their actions as justifiable or helpful in furthering their unethical conduct. Thus, individuals might rationalize fraudulent activities by convincing themselves that they are acting in the best interests of their organization (Avortri & Agbanyo, 2021).

Prior studies show that academic dishonesty (in varying forms, including AI) may be rationalized when students justify their action as relatively harmless to them; that is, they call it victimless, or they may call it a necessary compromise for achieving success in a competitive context of academia. Bilen and Matros (2021) have shown that whenever cheating was discussed during the pandemic, students would justify it by claiming that everyone does it, thus, diffusing their wrongdoing. Likewise, Ratmono and Frendy (2022) have shown that AI cheating is perceived by students to carry lighter ramifications compared to traditional cheating and, therefore, rationalize their actions, saying that technology is somehow eroding the walls of integrity. Lastly, Zayed (2023) has demonstrated that students conflate cheating with collaborative learning rather than traditional forms of cheating. Within the realm of their digitally-enabled study groups, they had anticipated their actions to be deemed acceptable. This mindset allowed them to justify their behavior and avoid negative self-perception.

Secondly, students justify cheating by externalizing the whole process toward external contingencies rather than trying to place the blame on themselves. Some external contingencies include hefty workloads, ineffective teaching, and peer or parental pressure. This external attribution permits them to save their self-esteem while succeeding in their dishonesty. For instance, Alshurafat et al. (2024) suggested that accounting students often justified their cheating with ChatGPT by suggesting that extreme pressure was placed on them to succeed in a highly competitive field. Hutton (2006) corroborated this assertion by stating that students sometimes justify cheating and other dishonest actions in response to perceived intolerable academic demands or unfair instructor support. This suggests that the perception of external pressure may compel students to rationalize cheating more than reasoning (whether concerning AI use or any other). Thus, in situations where students feel they have the right to emphasize good grades in a competitive environment with little support provided to them by instructors or organizations, they might rationalize cheating. Therefore, it can be hypothesized that:

H_3: The presence of rationalization significantly increases students' cheating behavior using artificial intelligence tools.

Capability and Intention to Misuse Artificial Intelligence

This final component of the fraud diamond-the ability, in turn, reflects a range of human attributes- such as intelligence, specialized knowledge in the areas relevant to the fraud, and the ability to cope with pressure that would enable a person to successfully carry out a fraud (Vousinas, 2019; Wolfe & Hermanson, 2004). This might include anything from the knowledge to bypass internal controls, the power to convince others to participate in the scheme, or access to sensitive information regarding the particular fraud. They hence find the gaps in the internal controls and exploit the flaws through technical expertise. The capability element, which includes the skills of the employees and the possibility of them engaging in fraud, is of great importance to the organization and auditors to discover potential fraudsters, employ effective preemptive control, and proficiently assign and reduce fraud risk (Omukaga, 2020;Vousinas, 2019).

This capability is a part and parcel of commission of fraud. Those who have the resources and skills to run their complex designs on it, e.g., would consist of people committing financial fraud (Kazemian et al., 2019). The ability is not the personal knowledge but the ability to influence and to rally others, who might be persuaded to be a part of a chain of engaging associates to the plot. Evidence of this correlation can be found in the previous researches: top management was, in the previous research, more disposed to fraud than middle or lower management (Utami et al., 2019). This implies that the more inclined to access resources, which are mostly promulgated by authority, the high ranking individuals are better placed to commit fraud. A positive correlation was created between perceived ability to conduct a fraud and the risk of committing a fraud by an individual person. Similarly, Kazemian et al. (2019) highlight the enabling role of capability in allowing individuals to identify and exploit flaws in internal control systems, therefore enhancing the probability of a fraud's success.

In the context of academic integrity, prior studies found that capability positively affects a person’s engagement in fraudulent actions. For example, Dias-Oliveira et al. (2024) found that a higher perceived capability to cheat predicted engagement in fraudulent academic behavior in students. Atmini et al. (2024) argue that students with more competency will likely engage in plagiarism. Therefore, it can be hypothesized that:

H_4: The presence of capability significantly increases students’ cheating behavior using artificial intelligence tools.

RESEARCH METHOD

Participants and Procedure

The study targeted business and accounting students in diploma and undergraduate programs across Indonesia. A non-probability sampling technique, specifically purposive sampling, was utilized to pick participants from eight universities both public and private across Java, Bali, and Sumatra. This option encouraged a high response rate because the survey link was handed over to students as part of class activities or sent directly to their email or WhatsApp accounts. The three islands are also selected because they constitute 79.15% of the Indonesian population (Badan Pusat Statistik Provinsi Sulawesi Utara, 2024). Students were obliged to give their email addresses and names to guarantee the integrity of the data and ward off multiple submissions. This enabled the researchers to skip the redundancy measure, thereby enhancing the data's accuracy and reliability.

In total, 461 responses were received in data collection from August 2024 – January 2025. Upon thorough consideration, we determined that 424 (91.97%) of the responses were eligible for various reasons and were therefore used in our study. The collected data was analyzed with SmartPLS version 4.1.0.9. PLS-SEM (Partial Least Squares Structural Equation Modelling) is software that measures the dependent and independent variables based on forecasting and estimation to maximize the explained variances (Arefin et al., 2015). It forecasts the absolute amount of fluctuations in endogenous constructs further to a group of exogenous constructs. The software has also been utilized previously in the research concerning academic dishonesty including Alshurafat et al. (2024) and Ofem et al. (2024) who both investigated AI in academic setting. This approach created useful information on the behaviors and attitudes of students on academic integrity in case concerning artificial intelligence.

A pilot study was conducted before the commencement of the primary data collection in the study, on selected samples of 20 students with different demographic backgrounds and academic backgrounds as would be envisaged in the actual research. The main study could not include data who has been collected during the pilot. Multiple pre-study objectives existed, among which are the minimization of a possible inaccurancy in the measurement and measurement bias (Podsakoff et al., 2012; Speklé & Widener, 2018), and evaluation of clarity and understandability of the questionnaire to the targeted respondents. Taking in consideration the comments on the pilot study, slight adjustments were done to the phrasing of the questions in the survey.

Research Model and Variable Operationalization

The questionnaire utilized in the research work was separated into three sections. The section questions the participants on the demographics of the population which are the key variables of importance, including age, gender, field of study and level of education. Last, the respondents are requested to list their higher education institutes such that the analysis can be done on an institutional basis.

The second section of the questionnaire explores factors that meet the decision to misuse AIs in order to commit academic dishonesty and fits into the framework of the fraud diamond theory. Sample measures used to determine variables were based on the research by Smith et al. (2023) and Smith et al. (2021), with a five-point Likert scale (one point to five points), where 1 was a strong disagreement, and 5 was a strong agreement. The first variable is opportunity, which is measured by four questions that determine the student in terms of feeling how common the AI misuse is amongst peers and in teaching/learning environments. The second variable, motivation, targets four items and requires students to consider their ideas of the benefits and the need to preserve academic outcomes using AI. The third variable is rationalization with three-item scale which will examine how the students rationalize the use of AI to obtain solutions on whether they perceive this as acceptable. Lastly, the capability variable has got three items that seek to determine, on the part of the student, the extent to which they are capable of accessing AI tools and using these tools in order to find solutions.

The third section of the questionnaire is directed at the behavioral intentions of students and their real engagement with AI in academic settings. Based on the measurement scales developed by Smith et al. (2023) and Smith et al. (2021), students' intention to use AI is measured by three items assessing their willingness to use AI tools to obtain solutions before submission. Their engagement with AI was then assessed with two items that directly asked if they used AI tools while completing academic work. A visual representation of the research model is depicted in Figure 1, while Table 1 provides a comprehensive outline of the operational definitions employed throughout the study.fore commencing the primary data collection, a pilot study was undertaken in selected groups of 20 students representing various demographic profiles and academic backgrounds envisioned for the actual study. Data collected during the pilot were not included in the analysis of the main study. The pre-study objectives were multiple, including the minimization of potential inaccuracies in measurement and measurement bias (Podsakoff et al., 2012; Speklé & Widener, 2018) and the evaluation of the clarity and understandability of the questionnaire to the targeted respondents. After gathering feedback on the pilot study, minor modifications were made to the wording of the questions in the survey.

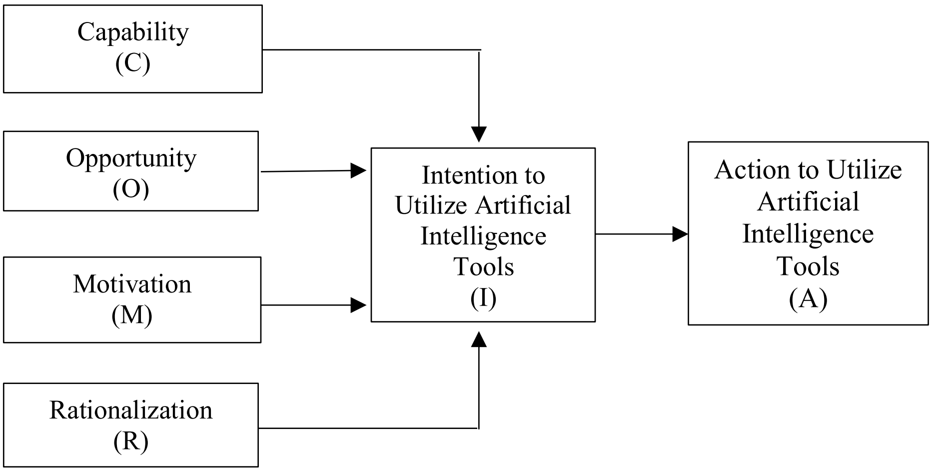

Figure 1. Research Model

Table 1. Operational Definition

Variable	Operational Definition	Indicators	Scale
Capability (C)	Capability relates to an individual's perception of their competence in identifying and exploiting opportunities to engage in fraudulent activities (Smith et al., 2023; Wolfe & Hermanson, 2004).	Three measurement items adapted from Smith et al., (2023), and Smith et al., (2021).	5-point Likert scale
Opportunity (O)	Opportunity refers to the perpetrator's opinion that there is a high likelihood of being able to willfully take advantage of a situation for personal gain, while also believing that the chances of being caught and facing negative consequences are minimal (Vousinas, 2019; Wolfe & Hermanson, 2004).	Four measurement items adapted from (Smith et al., 2023; Smith et al., 2021).	5-point Likert scale
Motivation (M)	Motivation refers to an individual's drive to participate in fraudulent actions, either to evade an unfavorable consequence, get a desirable result, or a combination of both, when a chance for deception presents itself and may be effectively pursued (Smith et al., 2023)	Four measurement items adapted from (Smith et al., 2023; Smith et al., 2021).	5-point Likert scale
Rationalization (R)	Rationalization pertains to an individual's rationale for taking advantage of opportunities to engage in fraudulent activities based on their evaluation of their skill and motivation (Smith et al., 2023).	Three measurement items adapted from (Smith et al., 2023; Smith et al., 2021).	5-point Likert scale.
Action to Utilize Artificial Intelligence Tools (A)	Action refers to the actual use of AI tools	Four measurement items adapted from (Sallam et al., 2023)	5-point Likert Scale

RESULTS AND DISCUSSION

Demographic Information

Table 2 reveals that a notable majority of the respondents, totaling 67.7%, were female, whereas male participants represented 32.3%. The demographic distribution indicates a possible preference towards female representation in the results. Additionally, a significant portion of the respondents, around 89.2%, were aged 19 or older, while 10.8% were under the age of 19.

Regarding educational background, more than half of the participants (73.1%) were involved in a bachelor's degree or a four-year diploma program, with a significant 77.1% of these students specializing in accounting. In terms of academic progression, a significant proportion (93.6%) were within their initial three years of study, whereas merely 6.4% had been engaged in their studies for over four years. Furthermore, a notable 94.3% of the participants indicated a Grade Point Average (GPA) above 3.00. The data indicates that our participant pool is well-matched with the target demographic for our study, thereby strengthening the credibility of our results.

Table 2. Demographic Profile

Characteristics	Frequency	%
Total respondent	424	100%
Gender		
Male	137	32.3%
Female	287	67.7%
Age		
17-18 years old	46	10.8%
19-20 years old	200	47.2%
≥ 21 years old	178	42.0%
Degree		
3-year diploma	114	26.9%
4-year diploma or bachelor	310	73.1%
Major		
Accounting	327	77.1%
Management	97	22.9%
Year of Study		
First year	112	26.4%
Second year	101	23.8%
Third year	131	30.9%
Fourth year	53	12.5%
More than four years	27	6.4%
GPA		
< 2.50	3	0.7%
2.50 – 2.99	21	5.0%
3.00 – 3.49	179	42.2%
≥ 3.50	221	52.1%

Source: Generated from field survey data utilizing Microsoft Excel (primary data).

Measurement Model Evaluation

A measurement model was tested at the item level to evaluate the adequacy of scale items as indicators of their underlying constructs. The measurement model identified six latent constructs: capability, opportunity, motivation, rationalization, intention to use artificial intelligence tools, and action to use artificial intelligence tools.

To ensure internal consistency, we computed Cronbach's alpha and composite reliability (CR), as presented in Table 3. All constructs' Cronbach's alpha and CR values were above the cut-off of 0.7, thereby confirming the reliability of the items employed in this study.

Second, convergent validity was determined on the basis of factor loadings and average variance extracted (AVE). The SmartPLS suggests limiting the minimum loading to 0.708, whereas the Average Variance Extracted (AVE) should not fall below 0.5 in order to accept the internal consistency of a particular construct (Hair Jr et al., 2020). As indicated by Table 3, all the items in the item were verified using both criteria, and the AVE of all the constructs exceeded 0.5. Average Variance Extracted (AVE) is defined as a measure of how much variance a construct accounts to in terms of its association with its measurements (Yoo & Alavi, 2001).

Table 3. Convergent Validity and Reliability Test Results

Construct	Items Loading	Factor Alpha	Cronbach's Reliability	Composite Extracted	Average Variance
Capability			0.784	0.786	0.697
	C1	0.830			
	C2	0.840			
	C3	0.835			
Opportunity			0.885	0.898	0.742
	O1	0.892			
	O2	0.874			
	O3	0.846			
	O4	0.832			
Motivation			0.757	0.770	0.573
	M1	0.715			
	M2	0.723			
	M3	0.772			
	M4	0.813			
Rationalization			0.735	0.747	**0.657**
	R1	0.859			
	R2	0.851			
	R3	0.713			
Intention to Utilize Artificial Intelligence Tools			0.892	0.893	0.822
	I1	0.904			
	I2	0.913			
	I3	0.903			
Action to Utilize Artificial Intelligence Tools			0.863	0.868	0.710
	A1	0.826			
	A2	0.854			
	A3	0.878			
	A4	0.810			

Source: SmartPLS version 4.1.0.9.

Moreover, we determined discriminant validity to ensure that each construct explains more variation within its indicators as compared to other constructs (Arefin et al., 2015). Table 4 points to the Fornell-Larcker Criterion that demonstrates the square root of the average of the variance extracted (AVE) of each construct shown on the diagonal is greater than the values in each row and column. Therefore, the discriminant validity of all the factors in the proposed model has been strongly supported by our results.

Table 4. Discriminant Validity (Fornell-Lacker Criterion)

Constructs	Capability	Opportunity	Motivation	Rationalization	Intention to Use Artificial Intelligence Tools	Action to Use Artificial Intelligence Tools
Capability	0.835					
Opportunity	0.488	0.861				
Motivation	0.685	0.610	0.757			
Rationalization	0.649	0.420	0.662	0.810		
Intention to Use Artificial Intelligence Tools	0.624	0.370	0.650	0.699	0.907	
Action to Use Artificial Intelligence Tools	0.642	0.592	0.686	0.669	0.745	0.842

Source: SmartPLS version 4.1.0.9.

Finally, we evaluated convergent validity by analysing the factor loadings and cross-loadings of all indicator items in relation to their respective latent constructs. Table V demonstrates that each item's cross-loadings reveal strong associations with their respective constructs and minimal associations with alternative constructs. The results indicated that all items loaded between 0.631 and 0.913 on their respective constructs. Thus, it can be concluded that these measurement items accurately represent their respective latent constructs.

Table 5. Discriminant Validity (Cross Loading Result)

Constructs / Items	Capability	Opportunity	Motivation	Rationalization	Intention to Use Artificial Intelligence Tools	Action to Use Artificial Intelligence Tools
C1	0.830	0.216	0.571	0.520	0.555	0.480
C2	0.840	0.446	0.549	0.526	0.468	0.534
C3	0.835	0.572	0.593	0.578	0.531	0.621
O1	0.450	0.892	0.565	0.425	0.364	0.578
O2	0.419	0.874	0.506	0.359	0.306	0.494
O3	0.350	0.846	0.459	0.302	0.246	0.458
O4	0.442	0.832	0.552	0.343	0.335	0.490
M1	0.481	0.766	0.715	0.466	0.424	0.579
M2	0.523	0.765	0.723	0.454	0.385	0.591
M3	0.528	0.236	0.772	0.518	0.539	0.461
M4	0.545	0.259	0.813	0.553	0.581	0.494
R1	0.601	0.419	0.611	0.859	0.610	0.599
R2	0.560	0.461	0.568	0.851	0.580	0.626
R3	0.400	0.111	0.416	0.713	0.504	0.382
I1	0.559	0.335	0.580	0.613	0.904	0.651
I2	0.567	0.321	0.614	0.656	0.913	0.650
I3	0.571	0.349	0.576	0.631	0.903	0.723
A1	0.550	0.454	0.548	0.508	0.631	0.826

A2	0.505	0.458	0.562	0.587	0.600	0.854
A3	0.570	0.516	0.614	0.621	0.690	0.878
A4	0.573	0.569	0.586	0.534	0.580	0.810

Source: SmartPLS Version 4.1.0.9.

Structural Model Evaluation

The results of this evaluation consisted of in-depth examinations of the standardized structural coefficients, that is, the beta values along with the t-values associated with those coefficients, used with the bootstrapping method laid down by Hair et al. (2020). This method was very rigorous, with 5,000 resamples. Subsequently, we assessed the explanatory value, which the R2 and effect size (f^2) of the model, which is discussed in the framework by Hair et al. (2020). The measures give an idea of the strength and the significance of the relationships in the model and extending further to the multidimensional explanatory power of the model.

Table 6 offers a compelling analysis to explain the factors contributing to students' intentions to engage with artificial intelligence in academic dishonesty. The findings show that three key determinants were significantly associated with this intention: capability (β=0.194; p=0.000), motivation (β=0.290; p=0.000), and rationalization (β=0.414; p=0.000). All of these factors positively influence students' decisions to engage in some form of dishonest practice, especially AI being misused in various forms for cheating. The support for H1, H3, and H4 means that as the students' capability for using AI increases, their intrinsic motivation also increases, and rationalizations for dishonest behaviour gain strength, thus increasing the likelihood for academic dishonesty. These effects strongly influence students' intention to misuse AI in realizing academic dishonesty (β=0.414; p=0.000). This empirical evidence, therefore, emphasizes a further critical point that with greater intention to misuse AI comes a greater likelihood of being engaged in dishonest actions. In contrast, the opportunity factor exhibits only a marginal effect on the intention to cheat using AI, with a p-value of 0.069. This means that while the opportunity may have some influence, it is not strong enough to be considered a determinant factor, leading to the rejection of hypothesis H2.

Table 6. Structural Model Test of Hypotheses

Hypotheses Path	Beta	t-values	p-values*	f^2
Capability → Intention	0.194	3.695	0.000	0.040[1]
Opportunity → Intention	- 0.074	1.820	0.069	0.008
Motivation → Intention	0.290	4.958	0.000	0.073[1]
Rationalization → Intention	0.414	7.700	0.000	0.194[2]
Intention → Action	0.745	25.833	0.000	1.246[3]

*$p < 0.05$
1Small effect size; 2Medium effect size; 3Large effect size

Source: SmartPLS version 4.1.0.9.

Figure 2 illustrates the structural model of the study, shedding light on the factors influencing students' intentions to use artificial intelligence for academic dishonesty. The adjusted R-squared value of 0.570 signifies that around 57% of the variance in these intentions is attributable to the collective influences of capability, opportunity, motivation, and rationalisation, highlighting their significance in shaping decision-making around academic integrity.

Additionally, students' intentions to use AI for dishonest purposes account for 55.5% of the variance in their actual cheating behaviors. This correlation underscores the importance of understanding intentions, as it serves as a predictor for actions. An adjusted R-squared value of 55.5% suggests a moderate correlation between intention and behaviour, indicating that as students' intents to cheat using AI rise, their propensity to engage in such behaviour also increases.

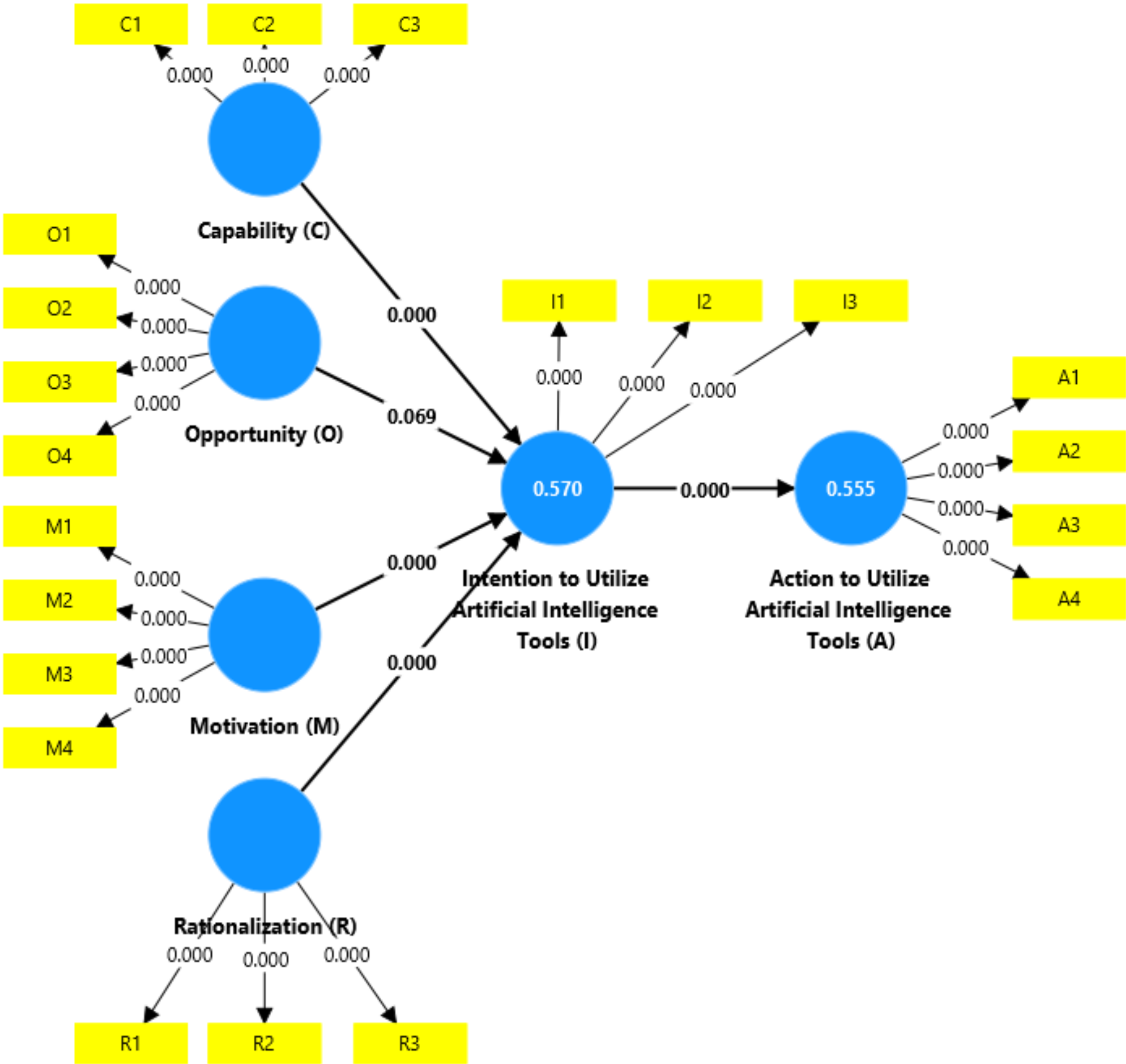

Figure 1. Structural Path Results

Discussion

The results of the study can provide the pivotal information about the abuse of the AI software by business and accounting students and demonstrate the complicated nature of academic dishonesty. To begin with, our study singles out three factors, capability, motivation, and rationalization, which are the primary sources of unethical behaviours in students. This can be explained by the findings of earlier researches, i.e. Alshurafat et al. (2024), Smith et al. (2023), Smith et al. (2021), and Sharma et al. (2024), that further prove the complexity of the issue.

The primary causes of academic misconduct by students are the competitiveness of academic life and the high expectations. Through the study, researchers indicate that some students do not consider it dishonest when they involve themselves in cheating, especially when facing immense pressure (Kock & Davison, 2003; Krou et al., 2020). In other words, cheating does not only apply to students who cannot perform well but also to students with high academic performance when they feel higher pressure, e.g. to meet scholarship criteria and tough competition. Consequently, AI technologies are becoming increasingly available for students since they greatly simplify dealing with their academic obligations, which in turn increases the use of shortcuts in the pursuit of success.

Another factor that significantly influences ethical decision-making is rationalization, which often acts to support unethical behaviour. For example, students may rationalize academic dishonesty on grounds of unfairness or perceive their rationalizations as justifications (Smith et al., 2021). Just as with Cheng and Crumbley (2018), students claim that unauthorized test banks are legitimate study aids while claiming they need to know the actual test questions. Thus, such rationalization makes students feel that their misconduct is not so serious. Rationalization serves students well in weighing the benefits of cheating (higher grades, less time) against the punishment they could incur if caught (Serhan et al., 2021). Ratmono & Frendy (2022) made important observations concerning historic ways of cheating now being weighed against methods employing AI tools, with students perceiving AI-assisted cheating as being less severe than traditional methods on the premise that technology has somehow dulled the boundary of academic integrity. So, this line of thought could potentially justify students committing academic dishonesty when they know it is wrong concerning academic integrity (Choo & Tan, 2008).

As our findings demonstrate, rationalization lowers the ethical barrier to academic misconduct, while the capability afforded by readily available AI tools provides the logistical means to undertake such actions. Just as with AI writing and paraphrasing tools that are available to students, there is a tendency for students to use these technologies for dishonest academic practice. These tools assist students in generating high-quality, plagiarism-free text, which usually is beyond their writing levels. However, while it is necessary to draw attention to the fact that AI is a worthy educational tool that can enhance skills like writing (Zulfa et al., 2023) and coding (Scharth, 2022), there are also legitimate concerns that increasing reliance on such tools will lead to total outsourcing of academic writing to AI (Sharma et al., 2024). For instance, Choi et al. (2022) revealed that ChatGPT might be useful for students to pass four courses. Hence, this interactivity in play provides an urgent call for wide discourse toward the inclusive thoughts and implications of AI in the academic environment. The findings here contrast with previous literature, which emphasizes a thematic association between opportunity and various forms of cheating: plagiarism (Sharma et al., 2024); online cheating (Bierstaker et al., 2024; Smith et al., 2023; Smith et al., 2021); AI misuse (Alshurafat et al., 2024). Herein, however, we argue that opportunity is not a determinant of students' decision to use AI for cheating. This aligns with recent work by Atmini et al. (2024), who found a lack of influence from opportunity on plagiarism rates.

This result may be explained by the fact that AI tools are standard, so "opportunity," in the usual sense, is no longer a barrier to use. Nonetheless, the rapidly increasing integration of AI in higher education (Sajja et al., 2024) offers a complex challenge to academic integrity. AI utility for easy learning becomes an issue when tools run an educational value for personalized learning pathways tailored to individual student needs

(Razia et al., 2022) and much more. The flip side of this technology can be used for dishonest means-obscurity in distinguishing between permitted help and academic dishonesty. Students who use AI for educational purposes may find it difficult to differentiate between right and wrong apps and may, therefore, cause unintentional or purposeful acts of academic dishonesty. The question of misuse arises due to the array of functionalities and easy availability of AI technologies, calling for urgent guidelines and ethical needs for deliberation on AI in education.

The second consideration is that students see access to AI as something they take for granted, reducing AI's ability to predict cheating behaviour. There was a survey carried out in 2024 with more than 3,500 students from 16 countries, which found that the vast majority, i.e., 86%, had used AI for academic purposes; more than half of the learners, i.e., 54%, were pretty regular users, applying AI during their daily or weekly studies (Rong & Chun, 2024). The extensive availability potentially creates a nearly universal opportunity, diminishing its role as a distinguishing feature in students' decision-making processes. For that reason, opportunities as historically and conventionally defined have become least relevant since these contexts often imply an event that is isolated, whereby conditions such as unsupervised examinations and access to another student's work become easily recognized. Henceforth, opportunities may mean something else, a ubiquitous element of the digital educational atmosphere, not only in an enabling context.

Meanwhile, the capacity of a student to utilize the AI tool enhances the influences on cheating, which is supported by arguments for committing dishonesty and academic pressure. For example, a student who is adept at AI usage has some rationale to excuse away ethical concerns and is under great pressure for grades will likely commit academic dishonesty regardless of the opportunities available to do so. Furthermore, if the detection of AI-generated text as plagiarism is perceived to be quite unlikely, that perception will lessen the seriousness of the risk in students' minds to a point where it overwhelms the lesser effect of any remaining opportunity available. Hence, while opportunity cannot be totally disregarded as a contributor, our evidence shows it is outweighed by other contributory factors in AI-assisted academic misconduct.

These AI tools are rising in educational practice; hence, a proactive posture on the institution's part is necessary to uphold academic integrity. Defining plagiarism to include all AI-generated content is impractical, considering AI's incorporation into widely used applications such as Microsoft Word and Grammarly. Technologies aid with writing mechanics, obscuring the distinction between student and AI-generated work. An effective alternative is to lay down proper ground rules for using AI in various assignments. For instance, lecturers might allow AI for brainstorming but prohibit it from being used to write the final submission. The statement of expectations in assignment instructions and rubrics now will enable tutors to keep academic integrity intact while harnessing the educative potential of AI.

AI literacy should be actively sought by both the professionals and students; they should know about the ethical side of the AI tools along with the mechanics. Although certain AI tools would help the students in their learning, like using grammar checkers, other tools would end up being taken advantage of in order to avoid the real learning process and that would be the case with these AI produced essays. Institutors should also be trained on how to detect AI-generated text and how to develop challenges that are difficult to manipulate using AI as well as how to initiate discussion about the morals of AI. The workshops on the responsible usage of AI-detection software and the results interpretation could also be helpful to the faculty.

Determine the adequate policies with regards to the acceptable application of AI and promote fair judgments to guard honesty. This can consists of online modules on AI and academic integrity and instructions on utilizing AI assistance when it is necessary. Institutions should also tap into software in order to focus on ethical adherence not necessarily on detecting plagiarism alone, but with the ability to notice any potential styles of AI misuse. This evidence may impact special interventions and campaigns. An example is that, when the students of certain course have a high AI utilization, teachers can be induced into revising their tasks and stimulating solid student work.

It is necessary to develop AI literacy among learners and instructors. This warrants the understanding of ethical consequences of AI tools and their functionality. Students should learn to differentiate between using AI to improve learning (e.g. strengthening grammatic) and using AI to avoid learning (e.g. AI-generated compositions). The teachers need to get prepared to recognize the AI-generated text, teach tasks and sessions that would reduce the AI-based misuse and provide sessions on AI-related ethics. The faculty could be provided with workshops on the use of responsible AI detection software and interpreting the results.

Institutions can also encourage academic integrity by setting up of simple policies on the use allowance of AI and giving access to material on ethical decision-making. This can be in the form of online courses about AI and academic integrity and how to use AI assistance when it is allowed. Software can also help institutions in checking the ethical compliance of the work not only identifying the plagiarism but also revealing the patterns of abusing AI. The data can assist focused intervention and education initiatives. As an example, teachers could be motivated to change tasks and motivate students to make genuine effort because of high rates of AI usage in a given course.

By establishing the conditions that promote openness and ethical interaction with AI, one can prepare students to live in the world of ubiquitous AI. It implies a shift towards more punitive approaches to academic misconduct to the one that encourages culture of learning and technology responsibilities. Open discussion regarding the ethical dilemmas surrounding AI provides an arena for students to make informed decisions about using AI tools. It develops their critical understanding of AI's impact on learning. This proactive approach may not only discourage academic dishonesty but also enables students to develop those critical thinking skills and ethical awareness to face the challenges imposed by the AI-driven world.

CONCLUSION

This research examines the factors influencing business accounting students' misuse of AI software in academic dishonesty, applying the Fraud Diamond theory. Our findings do not support previous studies that contend that opportunity is an important element in students' cheating. Rather, our findings made a relatively strong case that it does not influence the use of AI for academic dishonesty in any way. This may point to a plethora of AI tools being in the hands of the students, thus undermining the rationale of opportunity as a situational advantage. Opportunities are heavily weighed down by the overwhelming presence of AI. It is more about capabilities, rationalization, and motivation. A strong student in AI capabilities using rationalizations for cheating is highly motivated to succeed and likely will.

Our findings counter the preceding literature on academic dishonesty, which considers opportunity a primary determinant of students' cheating behaviour; in our study, opportunity was insignificant in making students choose to cheat using AI. The ready availability of AI tools is worth noting, which put a question mark on the traditional view of opportunity as situational advantage. In an AI-enabled environment, opportunity is no longer a distinguishing factor when predicting cheating behaviour. Capability, rationalization, and motivation matter far more. Students who are engaging or likely to engage in AI-supported academic dishonesty are likely to have skills in using AI tools combined with rationalizations that minimize ethical questions and a strong motivation to overcome obstacles.

The study has some implications for the academic debate. First, it shows that easy access to AI decreases opportunity as an important predictor of academic misconduct, enlarging the sphere for capabilities, rationalization, and motivation as stronger predictors. Second, unlike previous studies that looked at general academic misconduct or its mitigation, this study concentrated on the parameters that contributed to cheating by AI among Indonesian business students. Third, our results indicate a need for syllabus reform and the introduction of novel comfort technologies tailored to counter specific AI challenges. Using Indonesia as a case, it was presented as a model adaptable for other developing countries facing similar challenges.

Besides the ability to enrich the academic literature, the study is valued in practical terms. Coupled with active promotion of digital literacy and ethical decision-making to students, it outlines the critical necessity of the training courses on ethical AI application and academic integrity. Institutions should be able to give high support tools to the students facing the ethical dilemmas concerning the use of such technologies and to create proper guidelines on the appropriate use of artificial intelligence in learning institutions.

The findings of the research on the primary factors in AI-aided cheating, that are the capability, rationalization, and motivation, assist in designing more effective detection and prevention strategies. Knowledge of these factors assists organisations to develop specific intervention to promote responsible use of technology, assist in alleviating educational pressures and foster critical thinking ability to question reasons that justify unethical behaviour.

There are a number of limitations that this research has, which affect the conduct of a future study. It is a restricted sample to the Indonesian business and accounting students. Such a fine focus does restrict the generalizability of the results across student population groups, subjects and cultures. Future studies could ascertain greater and varied groups across other disciplines and cultures to enhance external validity and practicability. Another source of bias is a self-reported data used in the study. Students can cheat on AI more than they report trying to save themselves the undesirable consequences or appear appealing. This bias can distort the misuse of academic AI.

Objective measures which can be used in future studies to accompany self-reports include behavioural analysis, plagiarism checks, and analysis of work products by students to learn more about the phenomenon. Finally, the study is mainly concentrated on the issue of why students abuse AI, yet they hardly look at the impact, this behaviour will have long-term on their professional behaviour, ethics or learning. Future works can examine what the early access of studying AI-assisted cheating leads to regarding student perception of academic integrity, critical thinking abilities, and ethical decision-making in career choice.

Future research ought to assess the measures to promote ethical AI usage and reduce the number of cheaters. This may include the comparison of the educational interventions, which can promote digital literacy and ethical uses of AI, a technology focused on the inspection and prevention of AI-aided cheating, and regulatory adjustments, which may outline the implications and repercussions of a particular behaviour. Future research by circumventing such limitations and exploring these areas can offer a more detailed idea of how artificial intelligence, ethics, and business/accounting education interact so intimately. It will clear the way to the more rational and effective use of artificial intelligence in studying.

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