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AI's learning paradox: how business students' engagement with AI amplifies moral disengagement-driven misconduct

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ABSTRACT

Artificial intelligence (AI) in higher education creates a learning paradox, enhancing productivity while enabling hard-to-detect misconduct, challenging ethical boundaries, and university policies. Drawing on moral disengagement (MD) theory, this study examines how AI engagement conditions, captured by the Motive, Means, Opportunity (MMO) framework, amplify MD's effect on misconduct among graduate business students. Self-Regulated Learning (SRL) offers a learning process lens to locate where MD and its MMO conditions unfold within the learning cycle. Survey data from 226 UK-based students shows that MD predicts AI misconduct, with amplification from AI-related factors (usefulness, habit, obsessive passion, prompt engineering skill) and past misconduct. Policy enforcement mitigates this effect, while policy clarity is effective only when paired with enforcement. Unexpectedly, high-performing students are more likely to act on MD when scanning for misconduct opportunities. Our findings underline how AI engagement undermines ethical regulation, offering insights for institutional policy in AI-enabled learning environments.

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1. Introduction

Artificial Intelligence (AI) in higher education embodies a paradox: it empowers learning through enhanced productivity and enables difficult-to-detect academic misconduct, blurring ethical boundaries and challenging university norms (O'Dea 2024). In this evolving AI-enabled learning environment, more than 90% of university students use AI in their studies (Freeman 2025). AI accessibility and ease of use can drive students to seek and apply performance shortcuts, disrupting the ethical planning and self-reflection of self-regulated learning (SRL) (Cassidy 2011; Zimmerman 2002), which are critical for academic integrity. This concern is particularly relevant for business schools, where graduate students' 'bottom-line mentality' (McCabe, Butterfield, and Treviño 2006, 295) increases their propensity to cheat compared to some other majors (Tang and Chen 2008). However, engineering students have been shown to engage in similar levels of academic dishonesty as business students (McCabe 1997). While moral disengagement (MD) theory (Bandura 1999) helps us understand misconduct in higher education (Fida et al. 2018), we argue that AI introduces new challenges, amplifying its effects.

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Prior research has focused on AI-misconduct deterrents such as institutional sanctions (Zhang, Amos, and Pentina 2024). However, less attention has been given to how students' engagement with AI may amplify disengagement. Building on Treviño's (1986) interactionist model and the moral disengagement amplification literature (Moore 2015), we integrate the Motive, Means, Opportunity (MMO) framework (Pendse 2012) to capture personal and AI-related factors that shape the effect of moral disengagement on AI-enabled misconduct. Our conceptual model (Figure 1) combines MD with boundary conditions from the MMO framework, encapsulating the *why* (motive), *how* (means), and *when* (opportunity) of AI engagement. We propose that variations in AI engagement reflect student agency (Yang et al. 2024) and moderate the MD-misconduct relationship (Moore 2015).

Given its shared social cognitive theoretical roots with moral disengagement (Bandura 1991), SRL provides the conceptual scaffolding for the underlying learning process (Zimmerman 2002). Paradoxically, whereas SRL emphasizes the development of autonomous, goal-directed learning, moral disengagement reflects the erosion of self-regulation, which is further enhanced by certain MMO conditions that undermine the very purpose of learning. As much as AI may support aspects of SRL performance (Zimmerman 2002), when paired with MD, it can also disrupt SRL processes, ultimately facilitating ethically questionable behaviors. Using SRL as a learning process lens to interpret *where* MD unfolds to weaken self-regulation, we ask the following research question: How do personal and AI-related factors, as captured by the MMO framework, moderate the relationship between MD and AI-enabled academic misconduct?

This study contributes to AI-enabled higher education misconduct and policy literature in three ways. First, we extend MD theory by demonstrating how students' AI engagement amplifies the effectiveness of cognitive justifications for academic misconduct through SRL phases. Second, we adapt the MMO framework and distinguish between personal and AI-related factors, hypothesizing how AI-related motivations, means, and opportunities disrupt SRL learning processes and lead to academic misconduct. Third, we empirically validate these theoretical extensions using survey data from UK-based graduate business students. Notably, our findings reveal that AI habit plays a key role, policy clarity requires policy enforcement, and, surprisingly, high-performing students are more likely to activate their MD when scanning for AI misconduct opportunities.

2. Theory and hypotheses

Academic misconduct, influenced by individual and contextual factors, has long been a topic of concern for researchers and educators (Ashworth, Bannister, and Thorne 1997; Felski 2025;

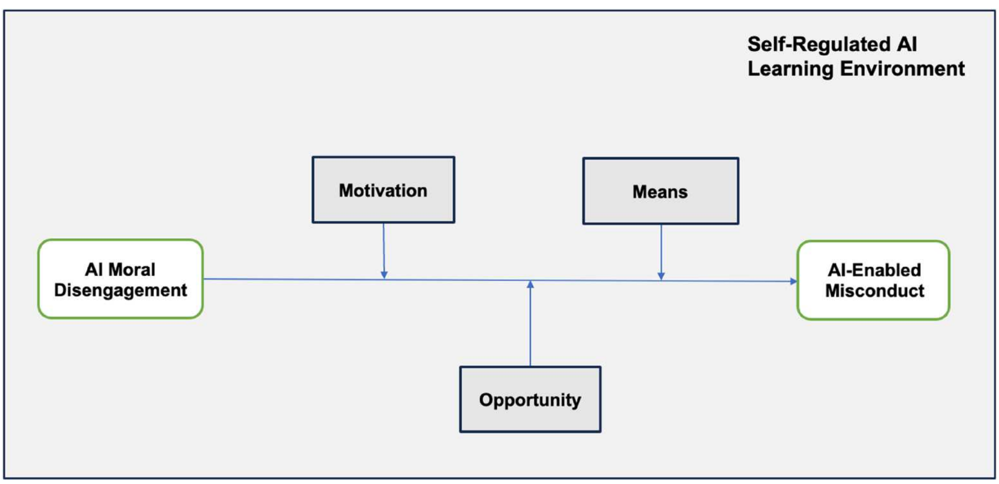

Figure 1. Conceptual model of misconduct in a self-regulated AI learning environment.

McCabe and Trevino 1997). While technology expanded plagiarism opportunities, from ‘cut-and-paste’ to contract cheating, rates had stabilized or even declined due to text-matching software and improved academic integrity education (Curtis and Tremayne 2021). However, the COVID-19 pandemic and shift to online learning disrupted this trend, with reported increases in academic dishonesty (Ives and Cazan 2024).

The literature often narrowly frames academic integrity around student misconduct, neglecting ethical ambiguity and the lack of consensus on what constitutes ethical academic behavior (Macfarlane, Zhang, and Pun 2014). In the era of ‘AI-giarism’, students hold diverse views on ethical AI use (Yang et al. 2024), questioning whether AI is an enabler of learning or misconduct, and prioritizing output production over genuine learning (Chan 2025; Essien et al. 2024). We define ‘AI-enabled misconduct’ as behavior that compromises the originality, transparency, or authenticity of student coursework, including failure to disclose or attribute AI-generated content, ‘humanizing’ AI outputs to evade detection, or knowingly violating university policy. Unlike previous technologies that primarily facilitated information access, AI fundamentally alters the creation process itself, producing original-looking content that more easily bypasses traditional detection methods without requiring substantial technical skill.

To develop our conceptual model, we integrate key misconduct frameworks (Table 1). As technology facilitates moral disengagement (MD) by creating psychological distance between actions and their consequences (Bandura 1999), misconduct must be understood through both cognitive and contextual factors (Treviño 1986). We build on the Fraud Triangle’s focus on rationalization (Cressey 1953) and the Fraud Diamond’s addition of capability (Wolfe and Hermanson 2004). The Fraud Diamond has also been applied to online academic misconduct (Smith et al. 2023). The MMO model reframes capability as ‘means’ (Pendse 2012) and encompasses AI-related conditions for academic misconduct, while MD provides internal justification.

To ensure conceptual clarity, we distinguish the synergistic roles of the frameworks utilized. Moral disengagement (MD) presents the core psychological mechanism for justifying unethical behavior, and MMO captures the situational moderating conditions explaining *why, how*, and *when* students engage in AI-enabled misconduct. Self-regulated learning (SRL) provides a different but complementary perspective by conceptually locating *where* these interactions between situational and psychological mechanisms unfold within the learning cycle. Although not directly measured in this study, SRL offers a learning process lens that describes students as proactive agents engaged in cycles of forethought (goal setting and planning), performance (task execution and self-monitoring), and self-reflection (evaluating outcomes) (Zimmerman 2002), explaining goal-directed learning. AI-enabled moral disengagement can disrupt these regulatory processes, creating ethical vulnerabilities. This disruption is particularly relevant for business education, where critical thinking, crucial for ethical reasoning, remains underdeveloped (Calma and Davies 2021).

Table 1. Review of theoretical frameworks for unethical behavior.

Theoretical frameworks	Key elements	Unique contribution	Limitations
Moral Disengagement (Bandura 1999)	• Cognitive Justification Mechanisms	Foundational theory for understanding ethical rationalization and its mechanisms	Does not include situational factors
Fraud Triangle (Cressey 1953)	• Pressure/Motive • Opportunity • Rationalization	Pioneering model identifying the three conditions for fraud	No explicit capability factor or rationalization mechanisms
Fraud Diamond (Wolfe and Hermanson 2004)	• Pressure/Motive • Opportunity • Rationalization • Capability	Recognizes skill/ability as essential for fraud	Lacks guidance on capability assessment or rationalization mechanisms
MMO (e.g. Pendse 2012)	• Motive • Means • Opportunity	A practical approach emphasizing ‘means’ (e.g. skills, resources)	Less focus on cognitive processes

This integration reveals how these frameworks complement each other in explaining AI-enabled misconduct, suggesting two contrasting pathways. On one hand, healthy self-regulated learning progresses from motivation through goal-setting and ethical reflection to authentic achievement. On the other hand, moral disengagement and MMO conditions can redirect students toward external pressures, cheating motives, and rationalized opportunity exploitation, undermining genuine learning.

2.1. Moral disengagement and unethical AI use

Moral disengagement, the cognitive process that enables individuals to justify unethical actions by suspending their internal moral standards (Bandura 1999), consists of eight cognitive mechanisms: moral justification, euphemistic labeling, making advantageous comparisons, displacing responsibility, diffusing responsibility, distorting consequences, dehumanizing, and attributing blame to others. These MD mechanisms (e.g. euphemistic labeling: 'AI is a productivity tool') distort the evaluative processes central to SRL's reflection phase (Zimmerman 2002), allowing students to justify misconduct rather than critically assess their actions against their learning goals. In particular, students may uncritically frame AI-enabled misconduct as a legitimate performance shortcut within AI-enabled learning; management education's emphasis on productivity gains and competitive advantage allows them to morally disengage and act unethically. Further, the low detectability of AI-generated text undermines the fear of sanctions, allowing students to more easily plan and act on their MD. As the association of MD and academic misconduct has been consistently demonstrated (Barbaranelli et al. 2018; Fida et al. 2018) and in line with Zhang, Amos, and Pentina (2024) who find MD to predict ChatGPT intent for plagiarism, we hypothesize that:

Hypothesis 1 (H1): *Moral disengagement will be positively associated with AI-enabled academic misconduct among students.*

2.2. The moderating role of motivation, means, and opportunity

2.2.1. Motivation: personal and technology-related

Recognizing the human-centric roots of MD and MMO, we consider the active role of technology within the individual's decision-making in the context of SRL processes. In the development of our hypotheses, we draw from moral disengagement theory and its underlying psychological mechanisms (Bandura 1999). We also draw from the technology adoption literature and identify usefulness (Davis 1989), obsessive passion, and habit for personal technologies (Mylonopoulos and Theoharakis 2020, 2021) as relevant factors for AI engagement. At the same time, individual factors, such as fear of failure, perceived performance, and past academic misconduct, remain relevant in shaping student misconduct (Choi 2021; Crocker et al. 2003; Cronan, Mullins, and Douglas 2018).

Fear of failure is an emotional and motivational trait that drives students to avoid negative outcomes like poor grades or failing (Choi 2021; Conroy, Willow, and Metzler 2002). It disrupts the forethought phase of SRL, where students set goals and appraise tasks (Zimmerman 2002), prioritizing achievement over learning (Ames and Archer 1988). Thus, fear of failure supports performance-avoidance goals and undermines adaptive planning, reinforcing students' views of AI as a shortcut to avoid negative outcomes. Such a mindset enhances the effect of MD mechanisms by prioritizing avoidance over authentic engagement with learning, making them more likely to engage in AI-enabled misconduct.

Perceived performance is a student's subjective assessment of their academic standing; low perceived performance threatens student self-worth, self-efficacy, and academic identity (Crocker et al. 2003; Richardson, Abraham, and Bond 2012), influencing the reflection phase of SRL where students assess past efforts (Zimmerman 2002). Low perceived performance triggers self-protective motives, shifting students to focus from learning to outcomes, framing unethical AI use as a pragmatic strategy to improve their standing. This personal motivation enhances the effect of AI-enabled misconduct justifications, amplifying the effect of MD mechanisms. Therefore, low perceived performance weakens ethical reflection, prioritizing performance over mastery and integrity, making students more likely to act on MD, increasing AI misconduct.

When previous academic success has been achieved through *past academic misconduct*, a strong motivational loop emerges, reinforcing it as an effective strategy (Skinner 1963). Over time, such a strategy impairs the reflection phase of SRL, where students evaluate their actions (Zimmerman 2002); a history of past misconduct normalizes unethical behavior and diminishes critical self-monitoring, making AI cheating a natural extension of past practices (McCabe, Butterfield, and Trevino 2012). Students with prior non-AI cheating experience (Fida et al. 2018) transfer similar justifications to AI-enabled misconduct, strengthening MD's effect. As undetected academic misconduct accumulates, acting on a set of distorted consequences becomes easier, weakening SRL's reflection phase and strengthening the link between MD and AI misuse, as students fail to critically assess ethical boundaries.

AI perceived usefulness, students' perception that AI tools are effective for academic tasks, is a key factor driving adoption (Budhathoki et al. 2024); a definition that draws from the well-established perceived usefulness concept (Davis 1989). When students find AI highly useful, they may engage more strategically with it, setting efficiency-driven goals as part of the forethought phase and selecting productivity-enhancing strategies during the performance phase (Zimmerman 2002). In the presence of MD, euphemistic labeling (e.g. 'AI is a productivity tool') can suppress the ethical dimensions of planning and monitoring. This further blurs the boundaries between cheating and legitimate AI uses, making SRL's planning and execution narrowly instrumental, with AI perceived usefulness amplifying MD's effect on academic misconduct.

AI obsessive passion, a compulsive urge to engage with AI tools (Mylonopoulos and Theoharakis 2020), makes AI part of a student's identity, disrupting students' SRL across all phases. It impairs forethought by distorting academic goal setting, weakens performance monitoring by reducing sensitivity to ethical cues, and undermines the reflection phase critical for self-judgment and corrective action (Zimmerman 2002). Students prioritize AI use at the expense of other values, such as ethical evaluation. This impaired reflexivity makes students more likely to act on MD mechanisms, amplifying the relationship between MD and academic misconduct.

AI habit, an automated recourse to AI tools triggered by contextual cues (e.g. assignment deadline) (Mylonopoulos and Theoharakis 2021; Wood and Rünger 2016), impacts SRL in the forethought and reflection phases. In forethought, habitual AI use can weaken ethical planning, distort self-motivation beliefs (e.g. inflating self-efficacy or diminishing task value for authentic learning), and reduce intentional strategy selection; in self-reflection, AI habit can impair self-judgment and causal attributions, rationalizing the negative effects of AI use on critical thinking, learning outcomes, and ethical standards (Zimmerman 2002). With less conscious deliberation, fewer cognitive resources for moral awareness and judgment are consumed (Ogunfowora et al. 2022), habituated behaviors are rationalized as harmless routines (Bandura 1999). The automaticity of AI habit undermines SRL's regulatory processes, strengthening the link between MD and misconduct as ethical considerations are ignored.

Overall, we hypothesize that:

Hypothesis 2 (H2): *The positive relationship between moral disengagement and AI-enabled academic misconduct will be stronger among students with high levels of motivation to use AI tools as defined by their (a) fear of failure, (b) lower perceived performance, (c) past academic misconduct, (d) AI usefulness, (e) AI obsessive passion and (f) AI Habit.*

2.2.2. Means: prompt engineering capability

Prompt engineering capability is the skill of crafting structured prompts and specific instructions with iterative refinement to generate desired AI outputs (Korzynski et al. 2023). Students who engage more purposefully with AI tools perform better (Nguyen et al. 2024), thereby enhancing

SRL's performance phase (Zimmerman 2002). However, as a 'Means' in our MMO framework, it can disrupt cognitive regulation (Boekaerts 1997), enabling unethical AI use. This aligns with findings that technical proficiency amplifies unethical technology use (Stylianou et al. 2013), allowing more opportunities and reducing detection risk (Cohen and Felson 1979). By improving output quality, competent prompt engineering may aid evasion and tilt the cost–benefit calculation toward misconduct (Cornish and Clarke 2014). Thus, students would euphemistically label their technical mastery as a productivity strategy, making them more likely to act on their MD. With prompt engineering providing the means to manipulate AI outputs, we hypothesize that:

Hypothesis 3 (H3): *The positive relationship between moral disengagement and AI-enabled academic misconduct will be stronger among students with high prompt engineering capability.*

2.2.3. Opportunity: policy clarity and policy enforcement

AI policy clarity, the perception of explicit and unambiguous institutional academic integrity rules regarding the use of AI (Gullifer and Tyson 2014), shapes SRL's forethought and reflection phases. In forethought, clear policies guide ethical planning; in reflection, they provide benchmarks for evaluation (Zimmerman 2002). As an opportunity factor in the MMO framework, policy clarity reduces ambiguity, limiting opportunities for MD mechanisms like attribution of blame (e.g. 'rules were unclear') (Bandura 1999), discouraging students from acting on moral justification (Cornish and Clarke 2014; Zhang, Amos, and Pentina 2024). Echoing findings that awareness efforts outperform detection-only strategies for reducing plagiarism (Prashar, Gupta, and Dwivedi 2024), policy clarity weakens the link between MD and AI-enabled misconduct.

AI policy enforcement, the consistent and rigorous application of sanctions (McCabe, Butterfield, and Trevino 2012), is based on deterrence theory, suggesting that cheating opportunities decrease as consequences become more severe and penalties are consistently applied (Zimring, Hawkins, and Vorenberg 1973). In the forethought stage of SRL, anticipated enforcement promotes ethical planning; in the reflection phase, it promotes accountability (ZImmerman 2002). Clear, enforced policies may reinforce SRL by enhancing metacognitive monitoring of ethical boundaries (Cassidy 2011). As an opportunity factor in the MMO framework, effective enforcement limits opportunities for misconduct by discouraging MD mechanisms like the distortion of consequences (Bandura 1999), weakening the link between MD and AI-enabled misconduct. Thus, we hypothesize that:

Hypothesis 4 (H4): *The positive relationship between moral disengagement and AI-enabled academic misconduct will be weaker when students perceive institutional policies on AI use as (a) clear and (b) effectively enforced.*

3. Methodology

We tested our hypotheses (Figure 2) based on a survey of 226 graduate business students enrolled in leading UK-based programs (April–July 2024). Ethical approval was obtained from one author's university prior to data collection. Participation was entirely voluntary, with students free to decline or withdraw at any time, and all participants provided informed consent before completing the survey. UK business schools are an appropriate testbed due to the UK's cohesive academic governance frameworks, such as the QAA guidelines (QAA 2025) and the rapid adoption of AI tools among university students. Participants averaged about 31.3 years, 50.4% male, and 38.9% employed full-time; these demographic factors were used as controls (McCabe, Treviño, and Butterfield 2001).

3.1. Measures

Participants were prompted to complete an online survey while in class (Table S1). The AI Moral disengagement (MD) scale was adapted from Moore et al. (2012), Fear of Failure (FF) was

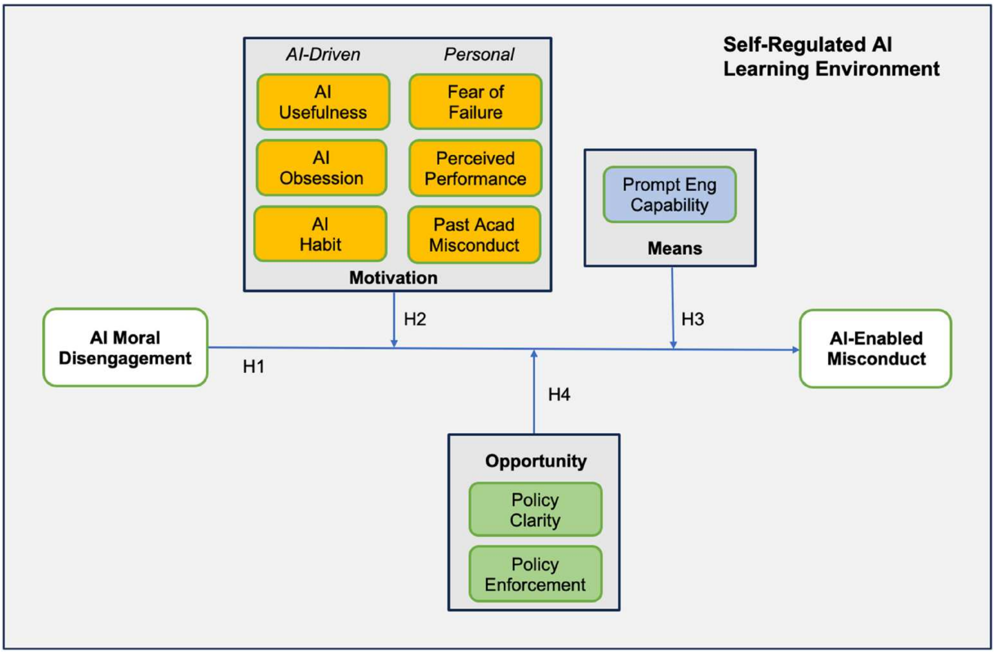

Figure 2. Hypothesized model of misconduct in a self-regulated AI learning environment.

adapted from Conroy, Willow, and Metzler (2002), Past Academic Misconduct (PAM) was adapted from Fida et al. (2018), Policy Clarity (PC) and Policy Enforcement Effectiveness (PEF) were adapted from McCabe, Butterfield, and Treviño (2006), AI Obsessive Passion (OP) adapted from Mylonopoulos and Theoharakis (2020), AI Habit (HB) and AI Usefulness (US) were adapted from Mylonopoulos and Theoharakis (2021). Performance Perception (PP) was a single-item scale indicating the perceived grade standing of the student, and AI Misconduct (AIM) was developed based on our definition.

Given that a scale for Prompt Engineering Capability (PENG) was not available, we developed one using guidance from OpenAI/ChatGPT (OpenAI 2024), Anthropic/Claude (Anthropic 2024), and Google/Gemini (Vergadia and Williams 2023). We synthesized the guidance provided and created items forming five main categories: (a) specifying tone/role, (b) guiding output (clarity/examples), (c) reference and documentation, (d) incremental approach, and (e) feedback and iteration. Its validity was confirmed through expert review by three academics who benchmarked it against technical skill constructs in prior literature (e.g. Weigel and Hazen 2014).

Self-reported measures of AI misconduct risk social desirability bias, as students may underreport unethical behavior (Randall and Fernandes 1991). We mitigated this through anonymity, neutral question framing, indirect questioning, and a robustness check by developing an AI Misconduct Scanning (AIMS) scale, adapted from Tang, Kacmar, and Busenitz (2012). This scale captures proactive scanning for AI-based cheating methods, which is less prone to underreporting. Per Routine Activity Theory (Cohen and Felson 1979), AIMS aligns with the forethought/planning phase of Self-Regulated Learning (SRL) (Zimmerman 2002), capturing strategic planning to unethically exploit AI, disrupting ethical goal setting.

All items were measured using 5-point Likert-type response scales; the resulting descriptive statistics of scale scores, as averages of their respective items, are reported in Table 2.

Table 2. Descriptive statistics, reliability, average variance extracted, and correlations

	M	SD	alpha	AVE	1	2	3	4	5	6	7	8	9	10	11	12
1.AIM	1.63	0.79	0.84	0.61	0.78											
2.AIMS	1.53	0.81	0.92	0.71	0.68	0.84										
3.MD	2.18	0.88	0.91	0.63	0.59	0.61	0.79									
4.US	3.45	0.99	0.93	0.73	0.47	0.43	0.50	0.85								
5.OP	1.78	0.90	0.89	0.82	0.40	0.43	0.45	0.44	0.90							
6.HB	2.26	1.23	0.95	0.91	0.65	0.54	0.59	0.62	0.59	0.95						
7.FF	2.60	1.04	0.89	0.68	0.26	0.31	0.22	0.22	0.08	0.15	0.83					
8.PP	3.50	0.74	-	-	0.01	0.05	−0.02	−0.10	0.00	0.02	−0.09	-				
9.PAM	1.54	0.71	0.77	0.53	0.43	0.43	0.45	0.23	0.18	0.27	0.26	−0.05	0.73			
10.PENG	2.72	1.05	0.94	0.64	0.47	0.42	0.39	0.61	0.46	0.59	0.17	0.04	0.17	0.80		
11.PC	4.07	0.87	0.87	0.70	−0.11	−0.14	−0.19	0.00	−0.04	−0.10	0.05	−0.04	−0.10	0.06	0.84	
12.PEF	2.94	1.08	0.90	0.77	−0.31	−0.23	−0.24	−0.22	−0.10	−0.29	−0.11	−0.08	−0.13	−0.22	0.04	0.88

Notes: Mean (M), Standard Deviation (SD), Average Variance Extracted (AVE), and square roots of AVE on diagonal. Moral Disengagement (MD), Fear of Failure (FF), Perceived Performance (PP), Past Academic Misconduct (PAM), AI Usefulness (US), AI Obsessive Passion (OP), AI Habit (HB), Prompt Engineering (PENG), Policy Clarity (PC), Policy Enforcement Effectiveness (PEF).

4. Results

We validated the measurement scales and conducted confirmatory factor analysis using Stata 18.5, which demonstrated a very good fit (χ^2/df = 2263.6/1578 = 1.43, CFI = 0.922, TLI = 0.916, and RMSEA = 0.044). Item loadings were significant, with average variance extracted (AVE) values above 0.5 and Cronbach alpha values exceeding 0.7 (Table 2), confirming reliability and convergent validity (Fornell and Larcker 1981). Discriminant validity was established as the square roots of AVE exceeded corresponding row and column values (Table 2). These findings indicate that although some motivators are correlated (e.g. AI Usefulness and AI Habit r = 0.62; AI Habit and Obsessive Passion r = 0.59), they remain statistically distinct constructs.

The study is based on self-reported data from a single source, so we assessed for common method variance (CMV) (Podsakoff et al. 2003). Harman's single-factor test confirmed CMV was absent, as a single factor did not explain the majority of the variance. With correlations between constructs less than 0.90 (Pavlou, Liang, and Xue 2007) and the highest variance inflation factor (VIF) at 2.5, below the commonly acceptable threshold of 3.3 (Kock 2015), provide further support for the absence of CMV bias. Additionally, interaction effects examined in this study are generally robust against CMV, which tends to deflate rather than inflate them (Siemsen, Roth, and Oliveira 2010). Thus, CMV does not pose a significant issue in our study.

We conducted regression analyses with robust standard errors to test our hypotheses. Standardized regression coefficients for AI Misconduct (Table 3) and AI Misconduct Scanning (Table 4) as dependent variables are presented, supporting most of our hypotheses (Models 1-10). The exceptions are Policy Clarity, which did not moderate MD with either dependent variable, and Fear of Failure and Perceived Performance moderated only with AIMS as a dependent variable. Unexpectedly, Perceived Performance enhanced the effect of MD on AIMS. To better understand the conditions that make PC an effective deterrent, we examined its simultaneous interaction with MD and PEF as a post hoc test, proving their significance for both dependent variables (Models 11). Moderation effect sizes were also calculated (Table 5).

5. Discussion and concluding remarks

This study investigates AI's learning paradox, examining how student motivations, means, and opportunities moderate moral disengagement's (MD) effect on AI-enabled academic misconduct, even though AI can also be effective in supporting self-regulated learning. We address our research question by extending MD with the MMO framework, also distinguishing between AI motivations (usefulness, obsession, habit) and personal motivations (fear of failing, performance perception, and past misconduct). We also introduce prompt engineering capability as a means, and institutional policy gaps in clarity and enforcement effectiveness as opportunities. In our investigation, we consider how the interaction of MD and MMO may erode regulation in different self-regulated learning (SRL) phases. For robustness, we also test AI misconduct scanning as an alternate outcome. Our results confirmed MD's positive association with both AI-enabled misconduct (H1) and AI misconduct scanning, aligning with previous research on MD's role in unethical behavior (Barbaranelli et al. 2018; Fida et al. 2018) and AI student misconduct (Zhang, Amos, and Pentina 2024).

We found support for AI usefulness, obsessive passion, habit, and past academic misconduct as moderators of MD (H2), with AI habit emerging as a particularly strong moderator (Table 5). AI usefulness underscores the practical value of generative AI tools (Noy and Zhang 2023), supporting the rationalization of risk/reward for AI misconduct. Similarly, AI obsessive passion embeds AI into the student's identity (Mylonopoulos and Theoharakis 2020), amplifying MD's effect by lowering the salience of ethical criteria and perceived risks. Habit's learned automaticity (Wood and Rünger 2016) prompts students to reflexively rely on AI for assignments, amplifying MD's effect on misconduct. Likewise, prior traditional cheating predisposes students to act on their MD, using AI unethically and scanning for new AI misconduct opportunities, reflecting the 'slippery slope' where repeated behavior reinforces MD (Cronan, Mullins, and Douglas 2018; Theoharakis, Voliotis, and Pollack 2021).

Table 3. Regression results (dependent variable: AI misconduct).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
MD	0.19** (0.08)	0.18* (0.08)	−0.04 (0.30)	0.20** (0.08)	0.16* (0.08)	0.17* (0.08)	0.16* (0.07)	0.17* (0.08)	0.19** (0.08)	0.17* (0.07)	0.17** (0.07)
FF	0.08 (0.05)	0.08 (0.05)	0.08 (0.05)	0.07 (0.05)	0.08 (0.05)	0.07 (0.05)	0.04 (0.05)	0.06 (0.05)	0.08 (0.05)	0.08 (0.05)	0.07 (0.05)
PP	0.01 (0.07)	0.01 (0.07)	0.00 (0.07)	0.01 (0.07)	0.00 (0.07)	0.00 (0.07)	0.00 (0.06)	−0.01 (0.07)	0.02 (0.07)	0.01 (0.07)	0.01 (0.07)
PAM	0.19** (0.07)	0.18* (0.07)	0.20** (0.08)	0.06 (0.09)	0.19** (0.07)	0.19** (0.07)	0.20** (0.06)	0.20** (0.07)	0.20** (0.08)	0.17** (0.07)	0.16** (0.07)
US	−0.02 (0.05)	0.00 (0.05)	−0.03 (0.05)	−0.01 (0.05)	0.05 (0.06)	0.00 (0.05)	0.04 (0.05)	0.00 (0.05)	−0.02 (0.05)	−0.01 (0.05)	−0.01 (0.05)
OP	−0.01 (0.06)	−0.01 (0.06)	−0.01 (0.06)	−0.03 (0.06)	−0.01 (0.06)	−0.04 (0.06)	−0.04 (0.05)	−0.02 (0.06)	−0.01 (0.06)	0.01 (0.06)	0.01 (0.06)
HB	0.38** (0.08)	0.37** (0.08)	0.38** (0.08)	0.39** (0.09)	0.34** (0.08)	0.36** (0.08)	0.29** (0.07)	0.33** (0.08)	0.37** (0.08)	0.32** (0.08)	0.29** (0.08)
PENG	0.11 (0.06)	0.11 (0.06)	0.10 (0.06)	0.13* (0.06)	0.12* (0.06)	0.13* (0.06)	0.16** (0.06)	0.19** (0.06)	0.11 (0.06)	0.12* (0.06)	0.14* (0.06)
PC	−0.03 (0.05)	−0.03 (0.05)	−0.02 (0.05)	−0.02 (0.05)	−0.03 (0.05)	−0.04 (0.05)	−0.06 (0.04)	−0.03 (0.05)	−0.02 (0.05)	−0.02 (0.05)	−0.09* (0.05)
PEF	−0.09* (0.05)	−0.10* (0.05)	−0.10* (0.05)	−0.07 (0.04)	−0.08* (0.04)	−0.09* (0.05)	−0.06 (0.04)	−0.09* (0.04)	−0.10* (0.05)	−0.13** (0.05)	−0.14** (0.05)
MDxFF		0.08 (0.07)									
MDxPP			0.07 (0.09)								
MDxPAM				0.18** (0.05)							
MDxUS					0.18** (0.06)						
MDxOP						0.12* (0.05)					
MDxHB							0.30** (0.06)				
MDxPENG								0.22** (0.06)			
MDxPC									0.03 (0.05)		−0.04 (0.04)
MDxPEF										−0.18** (0.06)	−0.19** (0.05)
PCxPEF											−0.14* (0.06)
MDxPCxPEF											−0.13* (0.06)
FT Employed	−0.08 (0.10)	−0.07 (0.11)	−0.07 (0.10)	−0.09 (0.10)	−0.09 (0.11)	−0.13 (0.10)	−0.11 (0.10)	−0.11 (0.11)	−0.09 (0.11)	−0.07 (0.10)	−0.09 (0.10)
Age	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.00)	−0.01 (0.01)	−0.01 (0.01)	0.00 (0.00)	−0.01 (0.00)	−0.01 (0.01)	−0.01 (0.00)	−0.01 (0.00)
Male	0.00 (0.10)	0.00 (0.09)	0.01 (0.10)	0.00 (0.09)	0.00 (0.09)	0.01 (0.10)	−0.02 (0.09)	0.01 (0.09)	0.00 (0.10)	0.00 (0.09)	0.02 (0.09)
Constant	0.20 (0.34)	0.18 (0.34)	0.21 (0.34)	0.09 (0.35)	0.10 (0.33)	0.14 (0.34)	−0.02 (0.30)	0.17 (0.33)	0.18 (0.34)	0.18 (0.32)	0.22 (0.31)
R-squared	0.55	0.56	0.55	0.58	0.58	0.56	0.62	0.59	0.55	0.59	0.61

Note: Values are standardized regression coefficients with standard errors in parentheses.

**$p < .01$, *$p < .05$, Moral Disengagement (MD), Fear of Failure (FF), Perceived Performance (PP), Past Academic Misconduct (PAM), AI Usefulness (US), AI Obsessive Passion (OP), AI Habit (HB), Prompt Engineering (PENG), Policy Clarity (PC), Policy Enforcement Effectiveness (PEF).

Table 4. Regression results (dependent variable: AI misconduct scanning).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
MD	0.28** (0.07)	0.25** (0.07)	−0.33 (0.25)	0.29** (0.07)	0.24** (0.07)	0.26** (0.08)	0.25** (0.07)	0.25** (0.07)	0.28** (0.07)	0.27** (0.07)	0.26** (0.06)
FF	0.14** (0.05)	0.14** (0.05)	0.13** (0.05)	0.13** (0.05)	0.13** (0.05)	0.12** (0.05)	0.10* (0.05)	0.11** (0.04)	0.14** (0.05)	0.14** (0.05)	0.13** (0.04)
PP	0.08 (0.06)	0.09 (0.06)	0.07 (0.06)	0.09 (0.06)	0.08 (0.06)	0.08 (0.06)	0.08 (0.06)	0.05 (0.06)	0.09 (0.06)	0.09 (0.06)	0.09 (0.06)
PAM	0.18** (0.07)	0.16** (0.06)	0.19** (0.07)	0.04 (0.06)	0.18** (0.07)	0.18** (0.07)	0.19** (0.06)	0.19** (0.06)	0.19** (0.07)	0.16** (0.06)	0.15** (0.06)
US	−0.01 (0.06)	0.02 (0.06)	−0.02 (0.06)	0.01 (0.06)	0.07 (0.08)	0.02 (0.06)	0.04 (0.06)	0.02 (0.06)	−0.01 (0.06)	0.00 (0.06)	0.00 (0.06)
OP	0.10 (0.06)	0.10 (0.06)	0.10 (0.06)	0.08 (0.06)	0.11 (0.06)	0.07 (0.06)	0.08 (0.06)	0.09 (0.06)	0.10 (0.06)	0.12* (0.06)	0.12* (0.06)
HB	0.16* (0.07)	0.14 (0.07)	0.17* (0.07)	0.17* (0.07)	0.12 (0.07)	0.14 (0.07)	0.08 (0.06)	0.09 (0.07)	0.15* (0.07)	0.11 (0.07)	0.06 (0.07)
PENG	0.09 (0.05)	0.09 (0.05)	0.08 (0.05)	0.11* (0.05)	0.11* (0.05)	0.11* (0.05)	0.14** (0.05)	0.21** (0.06)	0.10 (0.05)	0.10* (0.05)	0.13** (0.05)
PC	−0.06 (0.05)	−0.06 (0.05)	−0.04 (0.05)	−0.05 (0.05)	−0.07 (0.05)	−0.07 (0.05)	−0.09* (0.04)	−0.06 (0.05)	−0.05 (0.05)	−0.05 (0.05)	−0.15** (0.05)
PEF	−0.02 (0.05)	−0.03 (0.05)	−0.03 (0.05)	0.00 (0.05)	−0.01 (0.05)	−0.02 (0.05)	0.01 (0.05)	−0.01 (0.05)	−0.02 (0.05)	−0.06 (0.06)	−0.07 (0.05)
MDxFF		0.17** (0.05)									
MDxPP			0.18* (0.08)								
MDxPAM				0.19** (0.04)							
MDxUS					0.19** (0.07)						
MDxOP						0.13* (0.05)					
MDxHB							0.25** (0.06)				
MDxPENG								0.30** (0.05)			
MDxPC									0.05 (0.05)		−0.04 (0.04)
MDxPEF										−0.17** (0.06)	−0.18** (0.05)
PCxPEF											−0.17** (0.05)
MDxPCxPEF											−0.18** (0.05)
FT Employed	0.07 (0.12)	0.08 (0.12)	0.08 (0.12)	0.06 (0.12)	0.05 (0.12)	0.01 (0.12)	0.04 (0.12)	0.03 (0.12)	0.06 (0.12)	0.08 (0.12)	0.05 (0.12)
Age	−0.01** (0.01)	−0.02** (0.01)	−0.01** (0.01)	−0.01** (0.01)	−0.01** (0.01)	−0.01* (0.01)	−0.01* (0.01)	−0.01** (0.01)	−0.01** (0.01)	−0.02** (0.01)	−0.02** (0.01)
Male	−0.13 (0.10)	−0.13 (0.10)	−0.11 (0.10)	−0.13 (0.10)	−0.13 (0.10)	−0.12 (0.10)	−0.15 (0.09)	−0.11 (0.09)	−0.13 (0.10)	−0.13 (0.10)	−0.11 (0.10)
Constant	0.20 (0.30)	0.17 (0.29)	0.24 (0.31)	0.09 (0.28)	0.09 (0.30)	0.13 (0.29)	0.02 (0.27)	0.16 (0.29)	0.17 (0.30)	0.18 (0.28)	0.24 (0.28)
R-squared	0.51	0.54	0.52	0.54	0.54	0.52	0.56	0.57	0.51	0.54	0.57

Note: Values are standardized regression coefficients with standard errors in parentheses.
**$p < .01$, *$p < .05$, Moral Disengagement (MD), Fear of Failure (FF), Perceived Performance (PP), Past Academic Misconduct (PAM), AI Usefulness (US), AI Obsessive Passion (OP), AI Habit (HB), Prompt Engineering (PENG), Policy Clarity (PC), Policy Enforcement Effectiveness (PEF).

In contrast, personal factors, like fear of failure (Choi 2021) and perceived performance (Fida et al. 2018), do not moderate MD's effect on AI misconduct. However, fear of failure and, surprisingly, higher academic performance, strengthen MD's effect on AI misconduct scanning. High-performing students may experience pressure as AI tools enable lower-performing peers to narrow performance gaps (Brynjolfsson, Li, and Raymond 2025), driving them to search for AI-enabled shortcuts to maintain their academic standing (Miller, Murdock, and Grotewiel 2017) and 'get it done at all costs' (McCabe, Butterfield, and Treviño 2006, 295). Alternatively, higher performance might be a result of existing AI prompt capability or AI use; however, the correlations in the sample from our particular context do not indicate this to be the case (Table 2). Thus, integrity interventions should address the challenges faced by both high achievers and struggling students. From an SRL perspective, high performers may prioritize performance over reflecting on AI's impact on authenticity (Zimmerman 2002). The fact that both fear of failure and perceived performance significantly moderate MD's effect on AI misconduct scanning, but not actual misconduct, suggests they may operate earlier at the forethought and planning stage in an AI-enabled learning environment. Enforcement may ultimately determine whether scanning translates into action.

Our study introduced prompt engineering capability (Korzynski et al. 2023) as a key means (H3), potentially making academic misconduct more effective and less detectable, significantly amplifying the relationship between MD and AI misconduct (Table 5), and aligned with prior research showing that technical capability lowers barriers to misconduct and enables rationalization (Stylianou et al. 2013). Prompt engineering sophistication can make academic misconduct less detectable.

Regarding opportunities (H4), policy clarity alone did not moderate MD's effect on misconduct or scanning, but enforcement deterred both (Table 5). These results converge with longitudinal evidence that moral – development interventions curb misconduct only when students internalize fairness norms (Prashar, Gupta, and Dwivedi 2024). It is also consistent with MD theory, which suggests that self-regulation responds less to informational cues like policy statements and more to tangible consequences (Detert, Trevino, and Sweitzer 2008). Policy clarity moderates MD only when paired with enforcement, reducing misconduct and scanning (Table 5). Thus, institutions must invest both in policy awareness and active enforcement to ensure that AI misconduct is monitored and consequential. This finding aligns with Birks and Clare (2023), who demonstrate that situational crime prevention approaches emphasizing both clear guidelines and consistent enforcement are effective in reducing AI-facilitated academic misconduct. From an SRL perspective, clear policies and enforcement guide ethical planning and the forethought phase, but also promote accountability in the reflection phase (Zimmerman 2002).

Overall, our study confirms that MD influences AI-enabled misconduct among graduate business students, uncovering several MMO factors as the moderators of this relationship. Among AI-related

Table 5. Moderation effect sizes (eta-squared).

	AIM	AIMS
MDxFF	0.008	0.055*
MDxPP	0.003	0.025*
MDxPAM	0.051*	0.099**
MDxUS	0.043*	0.038*
MDxOP	0.023*	0.027*
MDxHB	0.112**	0.080**
MDxPENG	0.069**	0.124**
MDxPC	0.002	0.005
MDxPEF	0.045*	0.040*
PCxPEF	0.027*	0.058*
MDxPCxPEF	0.024*	0.061**

Notes: ***$\eta2 = 0.14$ (large effect), **$\eta2 = 0.06$ (medium effect), *$\eta2 = 0.01$(small effect).

factors, habitual AI use and AI prompt engineering rise as the most effective moderators (see Table 5). Unexpectedly, higher-performing students showed an increased likelihood of scanning for AI misconduct opportunities. Finally, policy clarity and enforcement work synergistically in weakening the relationship between MD and AI misconduct, emphasizing the importance of robust institutional proactiveness and oversight.

While Self-Regulated Learning (SRL) is traditionally seen as a normative framework for academic success based on autonomous planning, strategic execution, and reflective evaluation (Zimmerman 2002), our findings suggest that AI engagement may erode and displace the goal of SRL phases from authentic learning to pursuing shortcuts to performance outcomes. Figure 3 reinforces our framing of SRL as a contextual lens and presents a conceptual mapping of how AI-related engagement factors may introduce ethical vulnerabilities across SRL phases. While AI is taking the role of a cognitive partner that can reinforce regulated learning, it can also enable *unregulated learning*, with behaviors that prioritize performance outcomes over self-reflection and moral self-regulation. This learning paradox blurs ethical boundaries, particularly when AI use becomes habitual, obsessive, or technically sophisticated. This reframing indicates SRL's vulnerabilities in protecting ethical learning, urging further research into agency, responsibility, and integrity in AI-enabled learning environments.

5.1. Theoretical implications

This study offers three theoretical contributions addressing AI's learning paradox by refining frameworks for understanding academic misconduct in higher education.

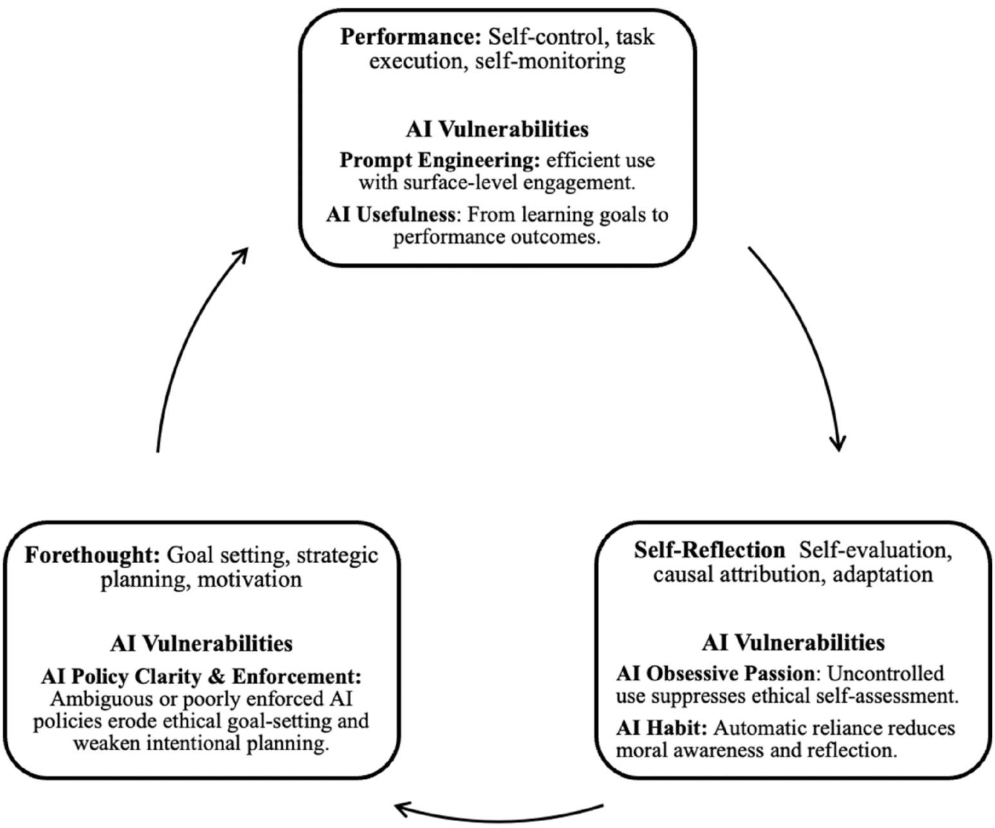

Figure 3. Conceptual mapping of ethical AI vulnerabilities across SRL phases.

First, it extends MD theory by integrating an AI-adapted Motive, Means, Opportunity (MMO) framework (Pendse 2012), which amplifies its effect (Bandura 1999; Moore 2015). Our MMO framework distinguishes between AI-specific and personal motives for misconduct and introduces prompt engineering capability as a novel form of 'means,' which enables technically skilled students to more effectively carry out unethical behavior.

Second, it reveals that only consistent enforcement, supported by clear AI policies, deters misconduct by countering the effects of AI-enabled rationalization (Chirikov, Shmeleva, and Loyalka 2020). Because of the paradoxical dual use of AI, enforcement plays a more central role in shaping students' AI ethical decision-making, offering insights for higher education theory and practice.

Third, it adds nuance to self-regulated learning (SRL) by highlighting how AI use may erode key regulatory processes. In this new AI-enabled environment, learning appears less regulated as technology can shift students' focus from learning to performance optimization, complicating assumptions about agency within SRL (Zimmerman 2002).

5.2. Limitations and future research

This study's findings are subject to boundary conditions. First, they apply to settings with evolving AI policies; stricter governance may weaken MD effects. Second, focusing on graduate business students, known for high levels of dishonesty, limits generalizability to disciplines like law or medicine with stronger ethical norms, nor do we know if AI misconduct replicates similarly across other disciplines (McCabe, Butterfield, and Treviño 2006). For example, computer science/engineering students may have a more natural ability to prompt AI, facilitating the execution of relevant academic tasks (e.g. writing a program) and have previously been found to exhibit considerable levels of academic misconduct (McCabe 1997). Third, the UK-based student sample may not extend to non-Western contexts due to cultural differences in integrity norms (Harrad, Keasley, and Jefferies 2024). Fourth, reliance on self-reported data, despite anonymity and robustness checks like AIMS, suggests future use of behavioral or experimental methods. Fifth, the cross-sectional design precludes causality; longitudinal or experimental studies manipulating policy or skills are needed. Sixth, while SRL was not directly measured in this study, it served as a process lens to interpret how moral disengagement and MMO factors may unfold across learning phases. Future research should directly measure the ethical erosion in SRL phases within AI-enabled learning environments to validate this theoretical positioning. Finally, future research should explore professional pressures on AI ethics to support innovation and integrity. Despite limitations, this study maps AI-specific factors and MD, laying an empirical foundation.

5.3. Implications for practice

This study provides actionable recommendations to enhance academic integrity in AI-enabled environments. First, universities should prioritize robust policy enforcement and clarity (Chirikov, Shmeleva, and Loyalka 2020). Second, institutions should adopt new AI-integrated assessments, or assessments that are immune to AI misconduct but can verify reasoning (e.g. oral presentations). Third, AI literacy training programs should be developed for both students and faculty, in line with international recommendations to build institutional capacity for managing AI in educational settings (Sabzalieva and Valentini 2023). Mandatory AI ethics modules that could help identify the ethical boundaries of acceptable AI use can reinforce reflective decision-making and reduce misuse (Essien et al. 2024). Fourth, universities should foster a learning-focused culture that emphasizes mastery, curiosity, and growth over performance metrics alone. Shifting institutional emphasis toward formative feedback and authentic engagement can help reduce this pressure and mitigate strategic misuse of AI. Beyond academia, AI misuse by business students may lead to workplace misconduct, necessitating explicit AI policies and accountability in high-risk areas like financial reporting; like students, professionals increasingly falsely claim

AI-enabled work as their own, raising questions about their at-work assessment (McRae 2025; Nonis and Swift 2001).

Disclosure statement

No potential conflict of interest was reported by the author(s).

Compliance with ethical standards

Ethical approval was obtained from one author's university, and the survey was pre-registered. Participants were fully informed of their rights, and data confidentiality was assured.

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