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REFRAMING ACADEMIC DISHONESTY IN THE DIGITAL ERA: THE INTERPLAY OF ETHICS, LEARNING HABITS, AND PERCEIVED DETECTION RISK

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ABSTRACT

The rapid digitalisation of higher education has transformed how students learn, simultaneously expanding opportunities for academic dishonesty, particularly through AI-assisted tools, online assessments, and technology-enabled collaboration. This study investigates the determinants of academic dishonesty by examining the roles of ethical perception, digital learning habits, and perceived detection risk, as well as the moderating influence of opportunistic behaviour on these relationships. Using data from 160 university students across Indonesia, the Philippines, Ghana, India, Kenya, Poland, and Thailand, this study employed Structural Equation Modelling (SEM-PLS) to analyse the direct and moderating effects within the proposed framework. The results show that ethical perception and perceived detection risk significantly reduce academic dishonesty, whereas instrumental digital learning habits increase the likelihood of misconduct. Opportunistic behaviour directly heightens academic dishonesty and partially mediates the effect of perceived detection risk. However, it did not moderate the relationships between ethical perception, digital learning habits, and dishonest behaviour. Instead, opportunistic behaviour significantly moderates the influence of perceived detection risk, indicating that students with strong opportunistic tendencies are less deterred by the possibility of detection. These findings highlight the complex interplay between moral awareness, technological behaviour, perceived surveillance, and exploitative tendencies in shaping misconduct. This study contributes to academic integrity research by integrating ethical, behavioural, and contextual elements into a comprehensive model, offering practical guidance for institutions seeking to strengthen integrity in digital learning environments.

1. Introduction

The rapid digitalisation of higher education has fundamentally reshaped students access to information, completion of assessments, and engagement with learning. Learning management systems, intelligent tutoring systems, and generative artificial intelligence tools are now embedded in many courses, particularly in business and management education (Fathy et al., 2025; Wiselee et al., 2025; Kalota et al., 2025). Alongside these opportunities, universities face growing concerns about new forms of academic dishonesty, including AI-assisted plagiarism, contract cheating in online environments, and technology-facilitated collaboration during remote exams (Rodrigues et al., 2025; Kann, 2025; Sharma & Bauman, 2025). These developments highlight the urgency of understanding whether academic dishonesty is increasing and why students choose to engage in unethical behaviour in technology-rich learning environments. Against this backdrop, the present study, titled “Reframing Academic Misconduct in the Digital Era: The Interplay of Ethics, Learning Habits, and Perceived Detection Risk,” seeks to examine how ethical, behavioural, and contextual factors jointly shape students’ propensity to violate academic integrity.

Academic dishonesty is a multidimensional phenomenon that encompasses cheating on examinations, plagiarism, falsification of data, unauthorised collaboration, and the misuse of digital tools to obtain an unfair advantage (Ilona et al., 2025; Telford & Tempowski, 2025). Research has consistently shown that such behaviour undermines learning outcomes, devalues qualifications, and erodes trust in educational institutions (Ehrmann et al., 2025; Vogt et al., 2025). Faculty members often report dilemmas and inconsistencies in responding to suspected dishonesty, which can further weaken the perceived legitimacy of integrity policies (Forbes, 2025). In parallel, ethical debates around dishonesty and liability in broader legal and societal contexts underscore that judgments about deceit are deeply shaped by context, norms, and institutional responses (Santatzoglou et al., 2025). Therefore, understanding academic dishonesty requires attention to both individual moral cognition and the wider digital and institutional environment in which students operate.

A central explanatory factor in this behavioural landscape is ethical perception, defined as how clearly and strongly individuals recognise academic misconduct as morally wrong.

Studies on academic integrity and research ethics show that stronger alignment with core scientific and educational values is associated with lower tolerance for questionable practices and misconduct (D. Li et al., 2025; Andersen, 2025). Educational and governance quality also appear to shape norms and attitudes toward integrity, suggesting that environments emphasising fairness, accountability, and the rule of law foster more ethical student behaviour (Artyukhov et al., 2025; Djankov et al., 2025). Interventions in graduate education aimed at promoting ethical authorship practices further indicate that perceptions of what is “acceptable” or “borderline” can be shifted through structured training and discussions (Demeter et al., 2025). In the context of student behaviour, it is therefore plausible that students with higher ethical perceptions will be less inclined to rationalise cheating or consider digital shortcuts as legitimate study strategies.

Simultaneously, digital learning habits have emerged as a key determinant of how students navigate opportunities and temptations in online and blended learning. Research on digital literacy and learning conditions shows that students’ habitual use of digital tools, whether oriented toward deep engagement or instrumental shortcuts, significantly affects their self-evaluated learning effectiveness (Kalota et al., 2025; Vaszkun & Mihalkov Szakács, 2025). Tang et al., 2025; Prabhavathy et al., 2025). However, framing AI and other tools primarily as efficiency enhancers can normalise practices that blur the line between acceptable assistance and academic misconduct (Rodrigues et al., 2025; Nasho Ah-Pine & Awuye, 2025). Therefore, digital learning patterns that emphasise speed, replication, and automation may be associated with higher levels of academic dishonesty, particularly when critical reflection and ethical guidance are weak.

Perceived detection risk is another crucial element in explaining dishonest behaviour. Deterrence perspectives suggest that when students believe that cheating is likely to be detected and sanctioned, the expected cost of misconduct increases, reducing their willingness to violate the rules. Analyses of institutional policies and enforcement mechanisms indicate that clear, comprehensive, and consistently applied academic integrity frameworks strengthen faculty confidence and student awareness of the consequences (Vogt et al., 2025; Forbes, 2025). In digital environments, the proliferation of plagiarism detection systems, proctoring technologies, and analytics-based monitoring has altered students' perceptions of how "invisible" cheating may be (Huy et al., 2025; Rodrigues et al., 2025). Simultaneously, public debates about surveillance, privacy, and the limitations of detection tools can create ambiguity about actual risks (Deng & Ahmed, 2025; Kamphorst & O'Neill, 2025). Understanding how students perceive detection risk in this complex technological landscape is essential for explaining their decisions to engage in academic dishonesty.

Beyond these cognitive and contextual factors, the literature on business ethics and corporate behaviour highlights opportunistic behaviour as a powerful driver of corporate misconduct. In financial and corporate settings, opportunism manifests in actions such as earnings management, opportunistic stock selling, misleading responses to fake news, and strategic greenwashing, often exploiting information asymmetries and regulatory gaps (Bratten et al., 2025; Sun et al., 2025; Wang et al., 2025; L. Li et al., 2025; Z. Li et al., 2025). Such Behaviour tends to persist even in the presence of formal controls when actors possess the motivation and creativity to circumvent them. Transposed to the educational arena, students with a stronger opportunistic orientation may be more inclined to exploit loopholes in assessment design, weaknesses in detection technologies, or ambiguous norms around AI use, regardless of their stated ethical beliefs or awareness of the rules (Ehrmann et al., 2025; Telford & Tempowski, 2025). Therefore, opportunistic behaviour may not only directly increase academic dishonesty but also weaken the protective effects of ethical perception and perceived detection risk.

Taken together, these strands of literature point to a complex interplay between ethical perception, digital learning habits, perceived detection risk, and opportunistic behaviour in shaping academic dishonesty in contemporary higher education. However, there remains a lack of empirical work that integrates these constructs into a single model and tests their relationships in diverse, technology-rich learning contexts across countries. To address this gap, this study has three objectives: first, to examine the direct effects of ethical perception, digital learning habits, and perceived detection risk on students' academic dishonesty; second, to investigate whether opportunistic behaviour moderates the relationships between these determinants and academic dishonesty; and third, to provide evidence-based insights that can inform institutional strategies for strengthening academic in digital learning environments. By focusing on these objectives, this study aims to bridge the insights from academic integrity research, digital learning scholarship, and the broader literature on opportunism and ethics in organisational settings. Based on the foregoing explanation and theoretical justification, the research questions guiding this study are as follows:

RQ1: Ethical perception is associated with academic dishonesty.

RQ2: Digital Learning Habits are associated with academic dishonesty.

RQ3: Perceived detection risk is associated with academic dishonesty.

RQ4: Opportunistic behaviour is associated with academic dishonesty

RQ5: Opportunistic behaviour moderates ethical perception, digital learning habits, and perceived detection risk on Academic Dishonesty

Recent research on academic integrity has expanded significantly; however, several gaps remain that warrant further investigation. Ilona et al. (2025) highlight that academic dishonesty among accounting students increased during the COVID-19 transition to online learning, emphasising how digital environments can unintentionally facilitate misconduct. However, their study focused primarily on contextual changes, leaving individual ethical and behavioural drivers underexplored. Rodrigues et al. (2025) provide a bibliometric analysis of artificial intelligence and academic integrity, showing rapid growth in AI-related misconduct but acknowledging that empirical evidence on students' actual behaviour and perceptions is still limited.

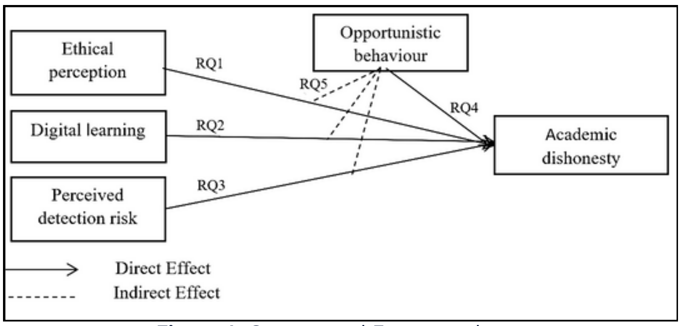

Figure 1: Conceptual Framework

Forbes (2025) examined faculty motivation to report suspected academic dishonesty, revealing inconsistencies in enforcement and suggesting that the perceived detection risk from the student perspective is poorly understood. Ehrmann et al. (2025) further demonstrate that peer influence and environmental factors significantly shape academic misconduct, yet they do not account for individual differences such as opportunistic tendencies. Collectively, these studies reveal three key gaps: the limited integration of ethical perception, digital learning habits, and perceived detection risk in a unified model; the absence of empirical testing across diverse digital learning environments; and the lack of attention to opportunistic behaviour as a potential moderator of these relationships. Addressing these gaps is critical for understanding academic dishonesty in technology-driven higher education.

2. Method

The present study employed a quantitative research design using a structured survey instrument distributed to university students across seven countries, namely Indonesia, the Philippines, Ghana, India, Kenya, Poland, and Thailand. The questionnaire was developed by adapting validated measurement items from prior studies and included five key constructs: Ethical Perception, Digital Learning Habits, Perceived Detection Risk, Opportunistic Behaviour, and Academic Dishonesty. All items were measured using a five-point Likert scale to accurately capture respondents' perceptions and behavioural tendencies. A purposive sampling technique was applied to target students who were actively engaged in digitally supported learning environments. A total of 160 valid responses were obtained after data screening, including checks for completeness, consistency and outliers.

Data were analysed using Structural Equation Modelling (SEM) with SmartPLS, which is suitable for predictive modelling and for studies with relatively small sample sizes. The analysis followed a two-step procedure, beginning with the assessment of the measurement model to ensure construct reliability, convergent validity, and discriminant validity. This was followed by the evaluation of the structural model to examine the hypothesised relationships among the variables. In addition to testing the direct effects of Ethical Perception, Digital Learning Habits, and Perceived Detection Risk on Academic Dishonesty, this study also assessed the moderating role of Opportunistic Behaviour. The SEM-PLS approach provided robust empirical insights into the determinants of academic dishonesty in digital learning contexts across diverse international settings.

3. Results and Discussion

Table 1. R-square value

	R-square	R-square adjusted
Y1.	0.854	0.85
Z1.	0.352	0.34

Source: processed data, 2025

The R-squared results show the predictive ability of the independent variables in explaining dependent constructs. The R-square value for Y1 is 0.854, meaning that 85.4 percent of the variance in Academic Dishonesty is explained by Ethical Perception, Digital Learning Habits, Perceived detection risk, and Opportunistic Behaviour. This value is considered to be very high, indicating that the model has a strong explanatory power. Meanwhile, the R-square value for Z1 is 0.352, which means that 35.2 percent of the variance in Opportunistic Behaviour is explained by the three independent variables. This falls into the moderate category, indicating an acceptable level of structural prediction.

Table 2. Reliability and validity test

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
X1.	0.899	1.138	0.918	0.693
X2.	0.871	0.939	0.9	0.646
X3.	0.996	0.996	0.997	0.984
Y1.	0.794	0.805	0.858	0.548
Z1.	0.844	0.954	0.88	0.595

Source: processed data, 2025

The reliability and validity results indicate that all constructs meet the requirements of convergent validity. The AVE values for all variables were above 0.50, showing that each set of indicators adequately represented its construct. The composite reliability coefficients were all far above the minimum threshold of 0.70, confirming strong internal consistency. Cronbach's alpha values are generally high, with X3 showing exceptionally large values owing to highly consistent indicators. Overall, the measurement model demonstrated good reliability and validity.

Table 3. Fornell-Larcker test

	X1.	X2.	X3.	Y1.	Z1.
X1.	0.833				
X2.	0.305	0.804			
X3.	0.344	-0.358	0.992		
Y1.	-0.27	0.517	-0.871	0.74	
Z1.	-0.151	0.356	-0.57	0.694	0.772

Source: processed data, 2025

The Fornell–Larcker results demonstrate that the square root of AVE for each construct is greater than its correlations with other constructs. Diagonal values such as 0.833 for X1 and 0.992 for X3 exceed the correlation values across rows and columns. This confirms that discriminant validity is achieved, meaning each construct is conceptually distinct and captures different aspects of the model.

Table 4. VIF Test

Indicator	VIF
X1.1	3.011
X1.2	1.927
X1.3	2.837
X1.4	2.37
X1.5	2.419
X2.1	1.974
X2.2	5.392
X2.3	2.853
X2.4	5.953
X2.5	2.567
X3.1	34.954
X3.2	32.859
X3.3	49.704
X3.4	41.382
X3.5	50.832
Y1.1	2.049
Y1.2	1.896
Y1.3	1.957
Y1.4	1.447
Y1.5	1.843
Z1.1	2.021
Z1.2	2.622
Z1.3	2.755
Z1.4	2.386
Z1.5	3.173

Source: processed data, 2025

Most indicators had VIF values below the recommended threshold of five. However, several indicators, particularly those under X3, show extremely high VIF values, ranging from 30 to 50. These high VIF values indicate very strong correlations among the indicators, suggesting redundancy or excessive similarity. Although the structural model may still run properly, such extreme multicollinearity signals the need to reevaluate the measurement items for X3. Despite this, if the model estimation remains stable and validity is achieved, the indicators can still be retained with caution.

Table 5. Model Fit

	Saturated model	Estimated model
SRMR	0.147	0.147
d_ULS	6.984	6.984
d_G	3.96	3.96
Chi-square	2.255.797	2.255.797
NFI	0.633	0.633

Source: processed data, 2025

The SRMR value of 0.147 indicates that the model fit is not optimal, as it exceeds the ideal threshold of 0.08. Other fit indicators, such as d_ULS and d_G, are within the acceptable ranges for PLS-SEM, which prioritises prediction accuracy rather than exact model fit. The NFI value of 0.633 reflects a moderate level of fit for the data. Although not high, it is still acceptable, given that PLS-SEM is not primarily designed for covariance-based fit assessment.

Table 6. Path coefficient

	Original sample (O)	T statistics (|O/STDEV|)	P values
X1. -> Y1.	-0.096	2.201	0.028
X1. -> Z1.	-0.044	0.591	0.555
X2. -> Y1.	0.239	6.105	0
X2. -> Z1.	0.196	1.937	0.053
X3. -> Y1.	-0.613	18.267	0
X3. -> Z1.	-0.484	6.782	0
Z1. -> Y1.	0.245	5.351	0

Source: processed data, 2025

The path coefficient results show that X1 has a negative and significant effect on Y1, with a coefficient of −0.096, t-value of 2.201, and p-value of 0.028, indicating that higher levels of X1 reduce Y1. However, X1 does not influence Z1 because its coefficient is −0.044, the t-value is only 0.591, and the p-value is 0.555, which is well above the significance threshold. Variable X2 has a positive and significant effect on Y1, indicated by a coefficient of 0.239, t-value of 6.105, and p-value of 0.000. However, the effect of X2 on Z1 is not significant, with a coefficient of 0.196, a t-value of 1.937, and a p-value of 0.053. Meanwhile, X3 demonstrates a very strong negative effect on Y1, supported by a coefficient of −0.613, t-value of 18.267, and p-value of 0.000. X3 also significantly affects Z1 negatively, as shown by a coefficient of −0.484, a t-value of 6.782, and a p-value of 0.000.

Furthermore, the mediator variable Z1 had a positive and significant effect on Y1, with a coefficient of 0.245, a t-value of 5.351, and a p-value of 0.000. These findings indicate that only X3 forms a complete mediation pathway through Z1, as it significantly influences both the mediator and dependent variables. In contrast, X1 and X2 do not significantly influence Z1, indicating that they do not exhibit indirect effects through the mediator. Overall, the results highlight that X3 and Z1 are the most dominant variables in the structural model, whereas the effects of X1 and X2 are limited to direct relationships with Y1 without mediation through Z1.

Table 7. Total indirect effect

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
X1. -> Y1.	-0.011	-0.01	0.019	0.575	0.565
X2. -> Y1.	0.048	0.048	0.028	1.727	0.084
X3. -> Y1.	-0.119	-0.117	0.026	4.6	0

Source: processed data, 2025

The results of the total indirect effects indicate that X1 does not exhibit a significant indirect influence on Y1, as reflected by its coefficient of −0.011, t-value of 0.575, and p-value of 0.565. Similarly, X2 shows a positive but insignificant indirect effect on Y1, with a coefficient of 0.048, a t-value of 1.727, and a p-value of 0.084, indicating that its mediation pathway through Z1 is not statistically supported. In contrast, X3 has a strong and significant indirect effect on Y1, with a coefficient of −0.119, a t-value of 4.600, and a p-value of 0.000. This finding confirms that X3 exerts both direct and indirect negative influences on Y1 through the mediator Z1, making X3 the only variable that achieves a meaningful mediated effect in this model.

4. Discussion

4.1 Ethical perceptions influence academic dishonesty

Ethical perceptions shape whether students view academic dishonesty as a serious moral violation or as a tolerable strategy for success, and this moral framing strongly influences their behaviour. Studies on character and peer influence suggest that when students perceive cheating as “normal” or situationally justified, their internal ethical barriers weaken, even if they understand that such behaviour is officially prohibited (Ehrmann et al., 2025; Ilona et al., 2025). Broader governance and integrity climates also matter: when education systems and institutions are seen as fair, transparent, and committed to integrity, students are more likely to internalise honesty as part of their identity (Artyukhov et al., 2025; D. Li et al., 2025). Conversely, if procedures, grading, or assessment are perceived as arbitrary or high-pressure, students are more likely to rationalise cheating as a response to systemic flaws rather than as a personal ethical failure. Faculty and policy responses reinforce these perceptions. When instructors are motivated and willing to report suspected dishonesty, and institutions back them with clear, consistent policies, students perceive a coherent ethical standard rather than a merely symbolic one (Forbes, 2025; Vogt et al., 2025; Demeter et al., 2025).

In digital and AI-mediated learning environments, ethical perceptions are being renegotiated rather than simply eroded. The rise of tools like ChatGPT, online exams, and metaverse-style platforms has led some students to recast certain forms of assistance as “smart use of technology” rather than cheating, especially when institutional guidance is ambiguous (Kann, 2025; Nasho Ah-Pine & Awuye, 2025; Rodrigues et al., 2025). Research on AI framing and academic integrity shows that if AI is presented mainly as a productivity enhancer without clear ethical boundaries, students may not perceive AI-assisted plagiarism or answer generation as genuinely dishonest (Deng & Ahmed, 2025; Fathy et al., 2025; Sharma & Bauman, 2025). Simultaneously, surveillance technologies, digital recording, and online proctoring can create a sense of being constantly watched, which may deter cheating but also shift perceptions toward viewing integrity as externally enforced rather than internally valued (Huy et al., 2025; Kamphorst & O'Neill, 2025). Overall, ethical perceptions influencing academic dishonesty are formed at the intersection of personal morality, peer norms, institutional integrity policies, and how new technologies are framed and governed in educational settings.

4.2 Digital Learning Habits' influence on academic dishonesty

Instrumental digital influence refers to how students use digital tools, platforms, and technologies as strategic means to achieve academic outcomes, including engaging in dishonest behaviour. Research shows that as digital literacy, learning habits, and technological familiarity increase, students may develop a more utilitarian view of digital resources, seeing them as tools to optimise efficiency, even in ways that compromise integrity (Vaszkun & Mihalkov Szakács, 2025). The widespread integration of AI systems, online learning platforms, and digital collaboration tools has blurred the boundaries between legitimate support and unethical assistance in academic work. For example, students who perceive AI-generated content as merely an extension of standard study aids may rationalise its use during assessments (Nasho Ah-Pine &Awuye, 2025; Rodrigues et al., 2025). Similarly, the normalisation of digital shortcuts in other domains, such as social media automation or AI-based decision support, can be transferred into academic contexts, fostering a mindset in which ethical considerations are secondary to performance outcomes (Deng & Ahmed, 2025; Y. M. Tang et al., 2025). This instrumental orientation toward technology increases the likelihood that students will justify dishonest digital practices as efficient, harmless, or even necessary.

Moreover, digital environments create new opportunities and pressures that shape students' decisions to act dishonestly in academic settings. Online exams, remote submissions, and AI-assisted writing tools have been found to lower the barriers to cheating by making dishonest strategies more accessible and harder to detect (Huy et al., 2025; Ilona et al., 2025). When institutional guidance on technology use is ambiguous or inconsistent, students may turn to digital tools instrumentally to cope with stress, workload, or unclear expectations (Kamphorst & O'Neill, 2025; Forbes, 2025). Peer norms also play a role: when students see others using technology opportunistically, whether through unauthorised collaboration, AI paraphrasing, or exploiting system vulnerabilities, the perceived acceptability of such behaviour increases (Ehrmann et al., 2025). Simultaneously, research shows that technologies designed to promote learning, such as intelligent tutoring systems or interactive digital environments, can inadvertently provide pathways for misuse when students prioritise outcomes over authentic learning (Wiselee et al., 2025; Chai-Arayalert & Puttinaovarat, 2025). Thus, the instrumental digital influence on academic dishonesty emerges not merely from tool availability but from the interplay between technological affordances, academic pressures, peer dynamics, and evolving ethical interpretations within digital learning ecosystems.

4.3 Perceived detection risk influences academic dishonesty

Perceived detection risk plays a central role in shaping students' decisions to engage in academic dishonesty, as it influences how risky or safe they believe dishonest behaviour to be. When students assume that surveillance is weak or that instructors rarely report misconduct, their perceived likelihood of being caught decreases, making cheating seem like a low-risk strategy (Forbes, 2025; Vogt et al., 2025). Digital learning environments amplify this dynamic relationship. In online settings where proctoring is inconsistent or technological loopholes exist, students may believe that detection mechanisms are easier to evade, thereby increasing their willingness to cheat (Huy et al., 2025; Ilona et al., 2025). Peer behaviour further shapes perceived detection: if students see others cheating without consequences, they infer that institutional monitoring is ineffective, which strengthens the perception that dishonest acts are unlikely to be punished (Ehrmann et al., 2025). This perception reduces the moral weight of misconduct, transforming cheating from an ethical dilemma into a calculated risk for the company.

Conversely, when detection is perceived as strong, consistent, and technologically supported, students tend to avoid dishonest behaviours because of heightened perceived consequences. Advanced monitoring systems, such as AI-driven proctoring, digital recording, and anomaly detection, can create a deterrent effect by signalling that misconduct is more visible and traceable (Kamphorst & O'Neill, 2025; Rodrigues et al., 2025). Institutional cultures that emphasise research integrity, clearly communicate academic policies, and demonstrate follow-through on misconduct cases also strengthen students' belief that rule violations will be detected and reported (Demeter et al., 2025; Z. Li et al., 2025). Even outside academic contexts, findings in business and finance research show that when oversight strengthens, opportunistic behaviours decline, suggesting a broader psychological pattern in how individuals respond to perceived monitoring (Cao & Zhang, 2025; Sun et al., 2025). Within academic settings, these insights imply that strengthening students' perception of detection through transparent communication, responsible use of technology, and consistent enforcement can meaningfully reduce academic dishonesty by shifting the perceived cost-benefit calculus associated with unethical behaviour.

4.4 Opportunistic behaviour is associated with academic dishonesty

Opportunistic behaviour reflects a willingness to exploit situations for personal gain, even when doing so violates established norms, and this tendency is closely associated with academic dishonesty. Research on ethical misconduct and opportunism in organisational and economic contexts shows that individuals who adopt an opportunistic mindset often prioritise outcomes over principles, rationalising rule-breaking when it serves their interests (Bratten et al., 2025; C. Tang et al., 2025). In academic settings, this mindset manifests when students treat educational processes as systems to navigate strategically rather than ethically. Studies on character, peer influence, and student decision-making indicate that when individuals believe they can benefit from dishonest shortcuts without jeopardising their goals, they are more likely to justify cheating as a practical solution rather than as a moral breach (Ehrmann et al., 2025; Ilona et al., 2025). Furthermore, environments perceived as competitive, high-pressure, or inconsistently monitored can intensify opportunistic tendencies by signalling that success is tied to outcomes rather than integrity.

The digital learning ecosystem further amplifies opportunities for opportunistic behaviour, making academic dishonesty easier to rationalise and execute. Research on AI use, online exam systems, and emerging educational technologies shows that students may exploit technological gaps or ambiguous policies to gain unfair advantages, especially when they believe that detection is unlikely or the consequences are minimal (Huy et al., 2025; Rodrigues et al., 2025). Studies exploring perceptions of AI reliability and digital assistance reveal that some students view these tools instrumentally, using them to bypass learning processes rather than to support them (Nasho Ah-Pine & Awuye, 2025; Deng & Ahmed, 2025). This mirrors the patterns observed in corporate contexts, where opportunistic behaviours emerge in response to weak oversight or flexible interpretations of rules (Cao & Zhang, 2025). Collectively, the literature suggests that opportunistic behaviour does not arise in isolation; it develops through the interaction of personal disposition, perceived risks and rewards, peer norms, and technological affordances, ultimately shaping a mindset that normalises academic dishonesty when it appears advantageous.

4.5 Opportunistic Behaviour Moderates Ethical Perception, Digital Learning Habits, And Perceived Detection Risk on Academic Dishonesty

The findings indicate that opportunistic behaviour does not moderate the relationship between ethical perceptions and academic dishonesty because ethical perceptions operate as a core moral judgment that is relatively stable and internalised. Students with strong ethical perceptions generally avoid dishonest practices regardless of opportunistic tendencies, as their moral evaluations create a psychological barrier against cheating (Ehrmann et al., 2025; Ilona et al., 2025). Conversely, students with weak ethical perceptions may rationalise dishonest behaviour even in the absence of opportunism because their moral framework does not clearly distinguish right from wrong in academic contexts (Artyukhov et al., 2025). This suggests that the influence of ethical perception on behaviour is grounded in moral cognition rather than situational exploitation, meaning that opportunistic behaviour has little room to amplify or weaken this relationship. Thus, ethical perception remains a direct and independent predictor of academic dishonesty.

Similarly, opportunistic behaviour did not moderate the effect of digital learning habits on academic dishonesty. Digital learning habits primarily reflect students' competencies, routines, and patterns of interaction with digital platforms, rather than their intentions to exploit these platforms (Vaszkun & Mihalkov Szakács, 2025). Whether students are digitally proficient or frequently rely on online tools is not inherently related to opportunistic tendencies, as the habitual nature of technology use is more strongly tied to convenience and learning style than to moral reasoning. Even when opportunistic tendencies exist, they do not substantially alter how digital habits translate into dishonest behaviour, because digital learning routines do not automatically create unethical motives (Nasho Ah-Pine & Awuye, 2025; Deng & Ahmed, 2025). Consequently, the pathway from digital learning habits to academic dishonesty remained consistent, regardless of opportunistic disposition, reinforcing that instrumentality and skill-related behaviours function independently of opportunistic exploitation.

In contrast, opportunistic behaviour significantly moderates the relationship between perceived detection risk and academic dishonesty. Students with low opportunistic tendencies tend to respond to a high perceived detection risk by avoiding dishonest acts and interpreting surveillance systems, proctoring tools, and integrity policies as credible deterrents (Forbes, 2025; Vogt et al., 2025). However, students with stronger opportunistic tendencies perceive detection risk differently; they are more inclined to search for loopholes, exploit weaknesses in monitoring systems, or rely on digital tools to obscure their misconduct (Huy et al., 2025; Kamphorst & O'Neill, 2025). Evidence from organisational and financial contexts similarly shows that opportunistic individuals often attempt to circumvent controls, even under heightened oversight (Cao & Zhang, 2025). Consequently, perceived detection risk becomes a meaningful deterrent only for students with lower opportunism, while high-opportunism students remain willing to take risks. This dynamic explains why opportunistic behaviour selectively moderates perceived detection risk but not ethical perceptions or digital learning habits in predicting academic misconduct.

5. Conclusion

The study concludes that academic dishonesty in digital learning environments is shaped by a complex interaction of ethical, behavioural, and contextual factors. Ethical perception significantly reduces dishonest behaviour, indicating that students with strong moral awareness are less likely to justify or engage in misconduct. Digital learning habits also influence dishonesty, especially when students adopt instrumental approaches to technology. Perceived detection risk emerges as a strong deterrent, directly lowering academic dishonesty and indirectly reducing opportunistic tendencies. Opportunistic behaviour is a significant predictor of dishonesty, demonstrating that students inclined to exploit loopholes are more likely to engage in unethical actions. However, this opportunism does not moderate the influence of ethical perceptions or digital learning habits, but it does affect how the perceived detection risk translates into dishonesty. These results highlight that while moral cognition and learning habits operate independently of opportunistic tendencies, risk perception interacts strongly with opportunism in shaping dishonest behaviour.

Based on these findings, universities should strengthen ethical education through sustained integrity training, clear communication of academic expectations, and reinforcement of fairness in assessment systems to help students internalise ethical norms in the academic environment. Institutions should also guide the responsible and reflective use of digital tools, ensuring that technology is framed as a learning aid rather than a shortcut. To address opportunistic behaviour, universities must enhance the visibility, consistency, and credibility of detection mechanisms, while providing transparent policies and enforcement practices. Simultaneously, detection systems should balance effectiveness with student privacy to maintain trust. Finally, institutions should design learning environments that reduce opportunities for exploitation through varied assessment formats, secure exam protocols, and proactive monitoring strategies. Together, these steps can strengthen academic integrity and reduce misconduct in increasingly digital learning environments.

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