WITHIN ARM'S REACH: DOES UBIQUITOUS SMART-DEVICE ACCESS DRIVE AI-ASSISTED CHEATING IN SOUTH KOREAN CLASSROOMS, OR IS IT A QUESTION OF ETHICAL PRACTICE?

Maidul Islam, Keimyung Adams College, Keimyung University, Daegu, South Korea,
email: maidul@kmu.ac.kr

Abstract: South Korea combines near-universal smartphone ownership, a highly competitive examination culture and rapid uptake of generative artificial intelligence (AI). This combination invites a pressing question: does easy access to smart devices make AI-assisted cheating more likely, or is the decisive factor the ethical practice that surrounds device use? This article reports a qualitative evidence synthesis that applies reflexive thematic analysis (Braun & Clarke, 2006) and thematic synthesis procedures (Thomas & Harden, 2008) to a purposively assembled corpus of 48 scholarly and policy sources on academic integrity, generative AI, digital behaviour and Korean education. Six themes were developed: ubiquitous access and low-effort opportunity; academic pressure and competitive culture; ambiguous norms and policy gaps; rationalisation and moral disengagement; detection limits and assessment design; and ethical literacy and institutional response. The synthesis supports a conditional answer. Access is a necessary enabling condition that lowers the cost of misconduct, but it is not a sufficient cause. Whether access becomes cheating depends on how pressure, perceived norms and rationalisation interact with assessment design and institutional clarity. A conceptual model and stakeholder implications are proposed. Because direct Korean empirical evidence on AI-related cheating remains thin, the findings are presented as theory-building propositions to be tested through interviews and focus groups with Korean students and instructors.

Keywords: academic integrity, generative AI, ChatGPT, smart devices, South Korea, qualitative synthesis, moral disengagement, assessment design

1. INTRODUCTION

Few education systems are as digitally saturated and as examination-driven as South Korea's. Smartphone ownership in the country has been reported at about 95% of adults, among the highest worldwide (Silver, 2019), and Korean university students integrate the smartphone into nearly every part of daily life (Park & Lee, 2012). At the same time, Korean schooling is widely described as shaped by "education fever", an intense social investment in credentials and rank (Seth, 2002), reinforced by a large private tutoring sector (Bray & Lykins, 2012). When large language models such as ChatGPT became publicly available in late 2022, they entered this setting at a moment when a capable writing, coding and problem-solving assistant sat in every student's pocket (Stokel-Walker, 2022).

Scholars quickly warned that such tools could transform academic dishonesty. Early analyses argued that generative AI can produce coherent essays, solve problem sets and generate code in seconds, challenging traditional assessment (Cotton et al., 2024; Perkins, 2023; Rudolph et al., 2023). Others countered that the tools also offer legitimate learning benefits and that framing them solely as a threat is unhelpful (Kasneci et al., 2023; Lund et al., 2023; Sullivan et al., 2023). The debate therefore has two poles. One pole is a *technological-access* explanation: when a device that can complete an assignment is always within reach, misconduct becomes cheap, fast and hard to detect. The other is an *ethical-practice* explanation: the same device is neutral, and what matters is the moral reasoning, norms and institutional culture that govern its use.

This article examines that tension in the South Korean case. Rather than assuming either explanation, it asks how the literature on cheating, generative AI and Korean educational culture can be integrated to explain when device access translates into misconduct. Three research questions guide the analysis:

> RQ1. How does the literature portray the relationship between easy access to smart devices and AI-assisted cheating?

RQ2. Which cultural, motivational and ethical factors, particularly those salient in South Korea, shape whether access becomes misconduct?

RQ3. What institutional conditions appear to turn AI access into either integrity breaches or ethical, learning-oriented practice?

The contribution is threefold: a theoretically grounded qualitative synthesis for a context that is under-researched, a conceptual model that locates device access within a wider set of conditions, and practical implications for Korean educators and policy makers. The paper is explicit about its evidentiary limits, discussed in Section 4.5 and Section 7.

2. BACKGROUND AND LITERATURE REVIEW

2.1 The Korean digital and educational context

Korea's digital infrastructure and smartphone penetration make device access nearly universal among students (Silver, 2019). Research on Korean university students has linked heavy smartphone use to both social connectedness and risks of over-dependence (Park & Lee, 2012). In international assessments, Korean students are consistently high performers (OECD, 2023), which is part of why the country is so frequently studied as an exemplar of educational success. Yet this performance sits within a social structure in which educational attainment is tightly linked to status, and where families invest heavily in supplementary tutoring to maintain advantage (Bray & Lykins, 2012; Seth, 2002).

Cross-national cultural research characterises Korea as relatively collectivist with strong uncertainty avoidance (Hofstede et al., 2010). Such dimensions do not determine behaviour, but they help explain why rank, group comparison and fear of failure may amplify the perceived stakes of assessment, and why rule ambiguity can be especially uncomfortable. Korean teachers are also active interpreters of AI policy: studies show that their acceptance of educational AI depends on pedagogical beliefs and trust (Choi et al., 2023) and that leading teachers envision student–AI collaboration with carefully designed learning tasks (Kim et al., 2022).

2.2 Why students cheat: foundational research

Decades of research indicate that cheating is common and multi-causal. Large surveys in North American universities showed that a substantial share of students engage in some form of cheating and that perceived peer behaviour and institutional honour codes are among the strongest correlates (McCabe et al., 2001, 2012). Reviews identify individual factors (such as performance goals and low self-efficacy), situational factors (such as competition and perceived opportunity) and normative factors (such as peers' behaviour) as predictors (Murdock & Anderman, 2006; Whitley, 1998). Cizek (1999) similarly emphasised that cheating reflects a calculation of costs, benefits and legitimacy as seen by students.

Importantly for the present question, earlier digital technologies had already altered the *opportunity structure* of dishonesty. Digital cheating and copy-and-paste plagiarism were documented in schools well before generative AI (Ma et al., 2008), and cross-cultural work showed that students' understandings of what counts as plagiarism vary with educational background and expectations (Park, 2003). More recent research on contract cheating shows that misconduct is also shaped by assessment design and student satisfaction, not merely by availability of services (Bretag et al., 2019b, 2019a; Curtis & Clare, 2017; Newton, 2018). This body of work warns against technological determinism: new tools expand possibility, yet prevalence is moderated by context.

2.3 Generative AI and academic integrity

Since 2023, a rapidly growing literature has analysed generative AI in higher education. Systematic work on AI in education was already substantial before ChatGPT (Zawacki-Richter et al., 2019; Hwang et al., 2020; Holmes et al., 2019), and reviews after its release emphasise both promise and risk (Crompton & Burke, 2023; Kasneci et al., 2023). On integrity, several conceptual and early empirical pieces argue that generative AI makes it easy to produce original-looking text that evades conventional plagiarism checking (Cotton et al., 2024; Eke, 2023; Perkins, 2023). Lund et al. (2023) and Dwivedi et al. (2023) highlight that ethical, scholarly and policy questions are unresolved, while Sullivan et al. (2023) stress that universities need coherent guidance rather than blanket bans. Student-voice research in Hong Kong suggests that students are generally open to

using generative AI but are uncertain about boundaries and worried about overreliance (Chan & Hu, 2023), and Chan (2023) proposes policy frameworks that combine pedagogical, governance and operational dimensions.

2.4 Detection, assessment design and their limits

A frequent institutional response is detection. However, independent testing shows that available AI-text detectors are neither accurate nor reliable enough to serve as sole evidence (Weber-Wulff et al., 2023). Detectors may also be biased: Liang et al. (2023) found that they misclassify writing by non-native English speakers as AI-generated, a concern with obvious relevance for Korean students writing in English. Experiments indicate that paraphrasing can defeat detection (Khalil & Er, 2023) and that even experts have difficulty distinguishing AI-generated from human-written scientific abstracts (Gao et al., 2023). Earlier reviews of plagiarism detection likewise note the limits of text-matching approaches (Foltýnek et al., 2019). These findings shift attention toward assessment design and "assessment security" in a digital world (Dawson, 2021; Holden et al., 2021).

3. THEORETICAL FRAMEWORK

Four complementary perspectives structure the analysis. First, the *theory of planned behavior* proposes that intentions arise from attitudes, subjective norms and perceived behavioural control (Ajzen, 1991); easy device access can be read as raising perceived control, while ambiguous rules affect subjective norms. Second, the *technology acceptance model* explains why tools perceived as useful and easy to use are adopted widely (Davis, 1989), which clarifies why students embrace AI irrespective of ethical status. Third, *social cognitive theory* and the concept of *moral disengagement* describe how people deactivate self-sanctions through justifications such as displacing responsibility or minimising consequences (Bandura, 1986, 1999). Fourth, Rest's (1986) four-component model of morality (sensitivity, judgement, motivation and character) offers a lens for understanding why a student who has access may or may not act ethically. Together they imply that access influences *opportunity* and *effort cost*, whereas ethical practice depends on norm

perception and moral processing. The analysis tests this reading against the literature rather than assuming it.

4. METHODOLOGY

4.1 Research design

The study is a qualitative evidence synthesis with an interpretivist orientation. Following Thomas and Harden's (2008) approach to thematic synthesis, descriptive themes were first extracted from sources and then abstracted into analytic themes that address the research questions. Reflexive thematic analysis (Braun & Clarke, 2006) guided the iterative process of familiarisation, coding, theme construction, review and definition. This design was chosen because the question concerns meaning, motivation and norms, which are best understood interpretively, and because primary qualitative data on AI-related cheating in Korea are scarce.

4.2 Corpus construction

The corpus was purposively assembled to represent five domains: (a) generative AI and academic integrity; (b) foundational research on cheating and plagiarism; (c) theories of intention, technology adoption and moral reasoning; (d) the Korean and East Asian educational and digital context, including national data; and (e) detection and assessment-design research. Peer-reviewed journal articles, scholarly books, and authoritative institutional and survey reports were eligible. Sources were retained if they contributed analytically to at least one research question. This was not an exhaustive, protocol-driven systematic review in the sense of Page et al. (2021); no claim is made of complete coverage, and Table 1 summarises the resulting corpus of 48 coded sources.

Table 1

Composition of the Analytic Corpus by Source Domain

Source domain	n	%	Illustrative sources
Generative AI and academic integrity	11	23%	Cotton et al. (2024); Perkins (2023); Chan & Hu (2023)

Foundational cheating and integrity research	11	23%	McCabe et al. (2012); Whitley (1998); Bretag et al. (2019a)
Theoretical and conceptual frameworks	5	10%	Ajzen (1991); Bandura (1999); Rest (1986)
Korean/East Asian context and national data	8	17%	Seth (2002); Park & Lee (2012); Choi et al. (2023)
Detection tools and assessment design	8	17%	Weber-Wulff et al. (2023); Liang et al. (2023); Dawson (2021)
AI in education (general and teacher-focused)	5	10%	Zawacki-Richter et al. (2019); Crompton & Burke (2023)
Total	48	100 %	

Note. Counts derive from the author's classification of each source by its primary contribution. Seven further methodological sources (e.g., Braun & Clarke, 2006) informed the design but were not coded as data.

4.3 Analytic procedure

Each source was read closely, and segments relevant to access, motivation, norms, rationalisation, detection or institutional response were coded inductively, with sensitising concepts drawn from Section 3. Codes were clustered into candidate themes, reviewed against the full corpus, and refined until each theme was internally coherent and distinct. A source could contribute to more than one theme. Theme contributions were then tabulated (Figure 1) to show the evidentiary weight behind each theme. These counts are descriptive aids to transparency; they are not statistical estimates, and a larger count does not imply larger causal importance.

4.4 Trustworthiness and reflexivity

Trustworthiness was addressed using the criteria of credibility, transferability, dependability and confirmability (Lincoln & Guba, 1985), operationalised as recommended for thematic analysis (Nowell et al., 2017): an audit trail of coding decisions, deliberate search for disconfirming

evidence, and thick description of context. Following the reflexivity emphasis in qualitative reporting standards (Tong et al., 2007), the author acknowledges a prior expectation that the access-versus-ethics dichotomy is too simple, and that this expectation may have shaped theme construction. Because no human participants were recruited, no ethics approval was required; however, any primary follow-up study should obtain institutional review board approval and informed consent.

4.5 Limitations of the design

Three limitations are fundamental. First, the corpus is limited to what the author could identify, and the field is changing rapidly; developments after 2024 are likely to be under-represented. Second, few sources report primary empirical data from Korean classrooms on AI-related cheating, so some Korea-specific arguments extend general findings by analogy and must be treated as propositions. Third, the thematic counts reflect the author's coding, and a different analyst might classify sources differently. These limits make the paper a theory-building contribution rather than a prevalence study.

5. FINDINGS

Six themes were constructed (Table 2). Figure 1 shows how many sources contributed to each theme. Access (T1) and ambiguous norms (T3) drew on the most sources, whereas academic pressure (T2) rested on the smallest, though conceptually rich, body of work, much of it indirect for the Korean case.

Table 2

Themes Developed from the Synthesis and Their Korean Interpretation

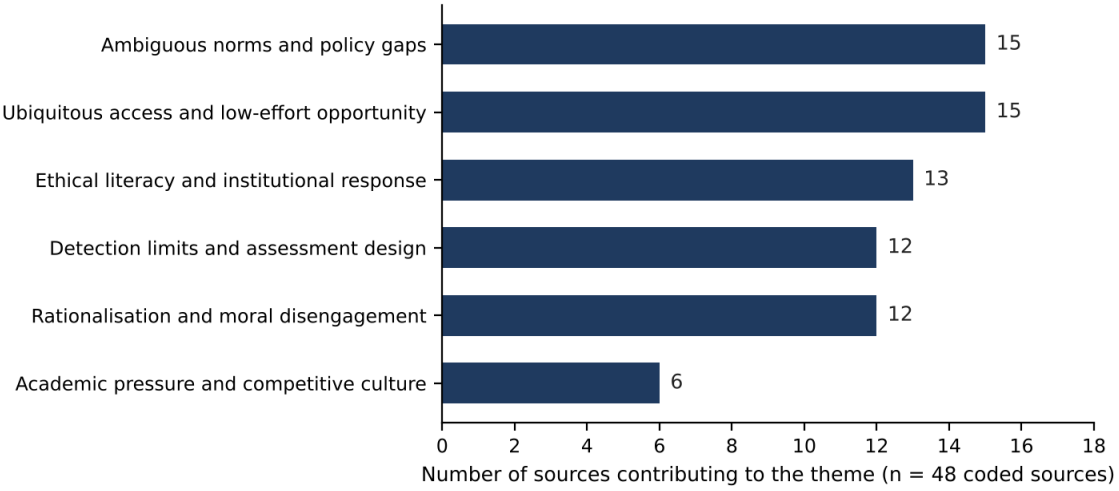
Theme	Definition	Korean interpretation	Key sources
T1. Ubiquitous access and low-effort opportunity	Always-available devices and free AI tools reduce the time, skill and risk needed to	Near-universal smartphone ownership and heavy daily use make access a given	Silver (2019); Park & Lee (2012); Cotton et al. (2024)

	produce acceptable work.	rather than a differentiator.	
T2. Academic pressure and competitive culture	Performance-oriented, high-stakes environments raise motivation to cheat.	"Education fever", rank sensitivity and private tutoring increase perceived cost of falling behind.	Seth (2002); Bray & Lykins (2012); Murdock & Anderman (2006)
T3. Ambiguous norms and policy gaps	Unclear rules and inconsistent course-level guidance weaken subjective norms.	Instructors vary in AI acceptance; high uncertainty avoidance makes unclear rules more stressful.	Choi et al. (2023); Chan & Hu (2023); Hofstede et al. (2010)
T4. Rationalisation and moral disengagement	Students justify AI use as "just a tool", as universal practice or as necessary to compete.	Peer comparison may strengthen "everyone does it" reasoning (proposition, untested in Korea).	Bandura (1999); McCabe et al. (2012); Curtis & Clare (2017)
T5. Detection limits and assessment design	Detectors are unreliable and biased; design-based approaches are more promising.	Non-native English writers risk false accusations; high reliance on exams may shift to take-home work.	Weber-Wulff et al. (2023); Liang et al. (2023); Dawson (2021)
T6. Ethical literacy and institutional response	Clear policy, AI literacy and learning-oriented task design channel use toward ethical practice.	Teacher trust and pedagogical belief are central to adoption; student–AI collaboration designs are emerging.	Kim et al. (2022); Chan (2023); Sullivan et al. (2023)

Note. Korean interpretations marked as propositions extend general findings and require empirical testing.

Figure 1

Number of Coded Sources Contributing to Each Theme



Note. Sources may contribute to more than one theme; counts are descriptive of the synthesis and do not indicate causal weight.

5.1 Theme 1: Ubiquitous access and low-effort opportunity

The literature leaves little doubt that generative AI lowers the effort of producing acceptable academic output. Commentators describe tools that draft essays, solve problems and write code within seconds (Cotton et al., 2024; Dwivedi et al., 2023; Stokel-Walker, 2022). Technology adoption theory explains why this ease is attractive: perceived usefulness and ease of use drive uptake (Davis, 1989), and AI tools score highly on both. In Korea, the structural precondition, near-universal device ownership (Silver, 2019), is already satisfied, and smartphones are woven into student routines (Park & Lee, 2012). Earlier digital cheating research suggests that convenience shapes behaviour: Ma et al. (2008) found technology-enabled copying to be common among school students, and contract-cheating work shows that availability of services expands misconduct (Bretag et al., 2019a; Newton, 2018). On this theme, the access explanation has real

support: access lowers the *cost* of cheating and widens the circle of those who could do it, including students who would have lacked the skill or nerve in earlier eras.

However, the literature simultaneously shows that access alone does not predict who cheats. Students who have used AI do not uniformly describe it as cheating, and many report using it for explanation, brainstorming or language support (Chan & Hu, 2023; Kasneci et al., 2023). Because virtually all Korean students have access, access cannot by itself explain *variation* in behaviour inside Korea; it works as a background condition. This is a crucial distinction: a constant cannot explain a variable.

5.2 Theme 2: Academic pressure and competitive culture

Motivational research consistently associates cheating with performance goals, fear of failure and perceived pressure to outperform others (Murdock & Anderman, 2006; Whitley, 1998). McCabe et al. (2012) similarly document that students cite pressure for grades and the high stakes of assessment. The Korean context intensifies these conditions. "Education fever" situates schooling as the main route to social mobility (Seth, 2002), and the shadow-education sector reflects families' efforts to secure relative advantage (Bray & Lykins, 2012). Under such conditions, a tool that promises higher grades at lower effort is attractive for strategic reasons independent of its mere availability. It is therefore plausible that pressure acts as a *motivational amplifier* that turns latent opportunity into attempted misconduct. Hofstede et al.'s (2010) cultural dimensions suggest that rank sensitivity and fear of failure may be pronounced, but the direct link to AI-related cheating in Korea is a proposition that needs empirical testing.

5.3 Theme 3: Ambiguous norms and policy gaps

A recurrent finding is that students and instructors lack a shared definition of acceptable AI use. Student-voice research reports uncertainty about boundaries (Chan & Hu, 2023), and policy scholars call for clear, differentiated guidance rather than blanket prohibition (Chan, 2023; Sullivan et al., 2023; Perkins, 2023). From the perspective of the theory of planned behavior, unclear subjective norms weaken the social signal that would otherwise restrain conduct (Ajzen, 1991). Research on plagiarism has long shown that perceptions of acceptable practice vary by background and context (Park, 2003), and McCabe et al. (2001) identified clear institutional codes

and peer norms as protective. In Korea, evidence indicates that teachers' stances towards AI differ with their pedagogical beliefs and trust (Choi et al., 2023), which suggests that students may encounter inconsistent expectations across courses. Where uncertainty avoidance is high (Hofstede et al., 2010), ambiguity may either encourage cautious abstention or, if peers appear to use AI freely, encourage conformity to the perceived majority; the literature does not resolve which dynamic prevails.

5.4 Theme 4: Rationalisation and moral disengagement

Bandura's (1999) mechanisms of moral disengagement, including moral justification, euphemistic labelling, displacement of responsibility and advantageous comparison, map closely onto the arguments reported for technology-assisted cheating. Students describe AI as "just another tool", compare it with calculators or spell-checkers, or argue that others do it so abstaining would be disadvantageous (Chan & Hu, 2023; Curtis & Clare, 2017; Ma et al., 2008). Cizek (1999) and McCabe et al. (2012) similarly describe how students neutralise guilt. Rest's (1986) model clarifies that the problem may arise at an earlier component: if students do not perceive undisclosed AI use as a moral issue (a failure of moral sensitivity), no deliberate rationalisation is even necessary. Access intensifies these processes because the act is private, quick and leaves little trace, making it easier to keep the self-image of an honest student intact (Bandura, 1986). In this sense, the ethical-practice explanation is not an alternative to the access explanation but the mechanism by which access either is or is not converted into misconduct.

5.5 Theme 5: Detection limits and assessment design

The synthesis shows that technical enforcement is a weak foundation. Detectors tested in controlled studies fall short of acceptable accuracy (Weber-Wulff et al., 2023), can be circumvented by paraphrasing (Khalil & Er, 2023) and show bias against non-native English writers (Liang et al., 2023). Human readers also struggle to separate AI from human writing (Gao et al., 2023). For Korean institutions where many students write in English as an additional language, reliance on detectors risks false accusations and erosion of trust. By contrast, research on contract cheating indicates that assessment design, including authentic tasks, process evidence and personalised components, is associated with lower risk (Bretag et al., 2019b; Dawson, 2021;

Holden et al., 2021). Rudolph et al. (2023) argue that generative AI exposes the weakness of traditional, product-focused assessment and invites redesign. This theme suggests that device access matters most where assessments are easily outsourced to a machine, and matters least where tasks require situated, observable or iterative performance.

5.6 Theme 6: Ethical literacy and institutional response

Finally, the literature points to institutions and educators as decisive. Policy frameworks recommend combining clear rules, AI literacy education and pedagogical redesign (Chan, 2023; Kasneci et al., 2023; Sullivan et al., 2023). Eaton (2021) argues for approaches to integrity that are educative rather than purely punitive. In the Korean setting, teacher perspectives are especially important: acceptance of AI tools depends on trust and beliefs about teaching (Choi et al., 2023), and expert teachers envision structured student–AI collaboration in which AI supports rather than replaces learning (Kim et al., 2022). Research on AI in online learning shows that AI can reshape learner–instructor interaction, with both opportunities and concerns (Seo et al., 2021). Taken together, these studies suggest that when students are taught *how* to use AI transparently, and when tasks reward learning processes, the same devices can support ethical practice rather than concealed substitution.

6. DISCUSSION

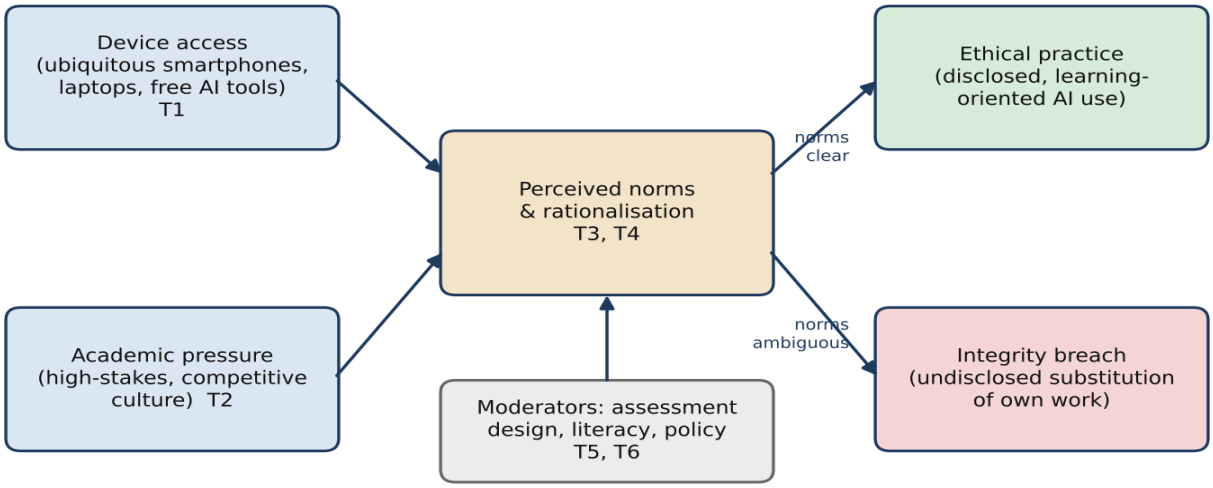
6.1 Answering the central question

The synthesis supports a *conditional* answer. Easy access to smart devices is a necessary enabling condition for AI-assisted cheating at scale, because it removes practical barriers (Theme 1). Yet in Korea, where access is almost universal, it cannot by itself explain who cheats. What differentiates ethical practice from misconduct is the interaction of pressure (Theme 2), perceived norms (Theme 3) and moral processing (Theme 4), moderated by assessment design (Theme 5) and institutional literacy (Theme 6). This reading is consistent with the broader integrity literature, which has repeatedly found that opportunity expands possibility while context determines prevalence (Bretag et al., 2019a; McCabe et al., 2012; Whitley, 1998). It also converges with the

theory of planned behavior: access raises perceived behavioural control, but intention depends equally on attitudes and subjective norms (Ajzen, 1991).

Figure 2

Proposed Conceptual Model: From Device Access to Integrity Breach or Ethical Practice



Note. T1–T6 refer to themes in Table 2. Arrows indicate proposed relationships derived from the synthesis, not tested causal paths.

6.2 The Korean particularities

Three features distinguish the Korean case. First, the access variable is saturated, so analysis must focus on motivation and norms rather than on a "digital divide" in cheating opportunity. Second, intense competition may increase the perceived payoff of AI assistance while making peer comparison especially salient, a plausible fuel for "everyone does it" rationalisation (Bandura, 1999; Seth, 2002). Third, the high value placed on examination performance means that institutions may be tempted toward surveillance and punishment, whereas the evidence suggests that detection-centred strategies are fragile and potentially inequitable for non-native English writers (Liang et al., 2023; Weber-Wulff et al., 2023). Each of these points is derived by applying general or adjacent findings to the Korean context, and each should be treated as a hypothesis for primary research.

6.3 Implications for practice

Table 3

Stakeholder Implications Derived from the Synthesis

Stakeholder	Recommended action	Themes	Grounding
Instructors	State course-level AI rules explicitly (permitted, permitted with disclosure, prohibited); redesign tasks to include drafts, oral defence and reflection.	T3, T5	Dawson (2021); Bretag et al. (2019b)
Universities and schools	Adopt coherent, educative AI policy; avoid sole reliance on detectors; provide appeals processes.	T3, T5, T6	Chan (2023); Weber-Wulff et al. (2023)
Students	Develop AI literacy and disclosure habits; practise reflecting on when AI supports versus substitutes learning.	T4, T6	Rest (1986); Kasneci et al. (2023)
Policy makers	Fund teacher training; support research on Korean students' AI practices; address pressure sources.	T2, T6	Choi et al. (2023); Bray & Lykins (2012)
Researchers	Conduct interviews and focus groups with Korean students and instructors; test the model in Figure 2.	All	Guest et al. (2006)

A key practical message is that restricting devices is neither feasible nor sufficient in a context of near-universal access; the more tractable levers are clarity of norms, the design of assessment and the cultivation of ethical judgement. This approach also aligns with calls to treat integrity as an educational goal rather than solely a compliance problem (Eaton, 2021).

7. Limitations and Directions for Future Research

Beyond the design limitations in Section 4.5, the synthesis inherits the weaknesses of its sources, including heavy reliance on conceptual commentary and early-stage studies of generative AI, and on self-report in the foundational cheating literature. The cultural arguments are necessarily coarse: national-level dimensions (Hofstede et al., 2010) cannot capture the diversity of Korean students across institution types, disciplines and regions. Future research should (a) conduct semi-structured interviews and focus groups with Korean secondary and university students and instructors, with sample sizes guided by saturation principles (Guest et al., 2006); (b) examine disciplinary differences, for example between engineering, humanities and language courses; (c) compare Korean institutions with clear versus ambiguous AI policies; (d) evaluate assessment-redesign interventions; and (e) update this synthesis as the post-2024 literature matures.

8. CONCLUSION

Does the easy accessibility of smart devices make cheating with AI more likely in South Korean classrooms, or is the issue ethical practice? The evidence synthesised here suggests that the question presents a false dichotomy. Access is the permissive condition; ethical practice is the governing mechanism. Because Korean students all but universally possess the devices, the explanatory weight shifts to pressure, norm clarity, moral reasoning and assessment design. Institutions that rely on bans or detectors risk misdiagnosing the problem, whereas those that combine transparent rules, AI literacy and learning-oriented tasks are better positioned to channel powerful tools toward ethical practice. The propositions advanced here should now be tested with primary qualitative data from Korean classrooms.

REFERENCES

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall.

Bandura, A. (1999). Moral disengagement in the perpetration of inhumanities. *Personality and Social Psychology Review, 3*(3), 193–209. https://doi.org/10.1207/s15327957pspr0303_3

Bray, M., & Lykins, C. (2012). *Shadow education: Private supplementary tutoring and its implications for policy makers in Asia*. Asian Development Bank.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Bretag, T., Harper, R., Burton, M., Ellis, C., Newton, P., Rozenberg, P., Saddiqui, S., & van Haeringen, K. (2019a). Contract cheating: A survey of Australian university students. *Studies in Higher Education, 44*(11), 1837–1856. https://doi.org/10.1080/03075079.2018.1462788

Bretag, T., Harper, R., Burton, M., Ellis, C., Newton, P., van Haeringen, K., Saddiqui, S., & Rozenberg, P. (2019b). Contract cheating and assessment design: Exploring the relationship. *Assessment & Evaluation in Higher Education, 44*(5), 676–691. https://doi.org/10.1080/02602938.2018.1527892

Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Education, 20*, Article 38. https://doi.org/10.1186/s41239-023-00408-3

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education, 20*, Article 43. https://doi.org/10.1186/s41239-023-00411-8

Choi, S., Jang, Y., & Kim, H. (2023). Influence of pedagogical beliefs and perceived trust on teachers' acceptance of educational artificial intelligence tools. *International Journal of*

Human–Computer Interaction, 39(4), 910–922. https://doi.org/10.1080/10447318.2022.2049145

Cizek, G. J. (1999). *Cheating on tests: How to do it, detect it, and prevent it*. Lawrence Erlbaum.

Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International, 61*(2), 228–239. https://doi.org/10.1080/14703297.2023.2190148

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education, 20*, Article 22. https://doi.org/10.1186/s41239-023-00392-8

Curtis, G. J., & Clare, J. (2017). How prevalent is contract cheating and to what extent are students repeat offenders? *Journal of Academic Ethics, 15*(2), 115–124. https://doi.org/10.1007/s10805-017-9278-x

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Dawson, P. (2021). *Defending assessment security in a digital world: Preventing e-cheating and supporting academic integrity in higher education*. Routledge.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., et al. (2023). Opinion paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, Article 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Eaton, S. E. (2021). *Plagiarism in higher education: Tackling tough topics in academic integrity*. Libraries Unlimited.

Eke, D. O. (2023). ChatGPT and the rise of generative AI: Threat to academic integrity? *Journal of Responsible Technology, 13*, Article 100060. https://doi.org/10.1016/j.jrt.2023.100060

Foltýnek, T., Meuschke, N., & Gipp, B. (2019). Academic plagiarism detection: A systematic literature review. *ACM Computing Surveys, 52*(6), Article 112. https://doi.org/10.1145/3345317

Gao, C. A., Howard, F. M., Markov, N. S., Dyer, E. C., Ramesh, S., Luo, Y., & Pearson, A. T. (2023). Comparing scientific abstracts generated by ChatGPT to real abstracts with detectors and blinded human reviewers. *npj Digital Medicine, 6*, Article 75. https://doi.org/10.1038/s41746-023-00819-6

Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field Methods, 18*(1), 59–82. https://doi.org/10.1177/1525822X05279903

Hofstede, G., Hofstede, G. J., & Minkov, M. (2010). *Cultures and organizations: Software of the mind* (3rd ed.). McGraw-Hill.

Holden, O. L., Norris, M. E., & Kuhlmeier, V. A. (2021). Academic integrity in online assessment: A research review. *Frontiers in Education, 6*, Article 639814. https://doi.org/10.3389/feduc.2021.639814

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.

Hwang, G.-J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of artificial intelligence in education. *Computers and Education: Artificial Intelligence, 1*, Article 100001. https://doi.org/10.1016/j.caeai.2020.100001

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., et al. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, Article 102274. https://doi.org/10.1016/j.lindif.2023.102274

Khalil, M., & Er, E. (2023). Will ChatGPT get you caught? Rethinking of plagiarism detection. In P. Zaphiris & A. Ioannou (Eds.), *Learning and collaboration technologies* (pp. 475–487). Springer. https://doi.org/10.1007/978-3-031-34411-4_32

Kim, J., Lee, H., & Cho, Y. H. (2022). Learning design to support student-AI collaboration: Perspectives of leading teachers for AI in education. *Education and Information Technologies, 27*, 6069–6104. https://doi.org/10.1007/s10639-021-10831-6

Liang, W., Yuksekgonul, M., Mao, Y., Wu, E., & Zou, J. (2023). GPT detectors are biased against non-native English writers. *Patterns, 4*(7), Article 100779. https://doi.org/10.1016/j.patter.2023.100779

Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry*. Sage.

Lund, B. D., Wang, T., Mannuru, N. R., Nie, B., Shimray, S., & Wang, Z. (2023). ChatGPT and a new academic reality: Artificial intelligence-written research papers and the ethics of the large language models in scholarly publishing. *Journal of the Association for Information Science and Technology, 74*(5), 570–581. https://doi.org/10.1002/asi.24750

Ma, H. J., Wan, G., & Lu, E. Y. (2008). Digital cheating and plagiarism in schools. *Theory Into Practice, 47*(3), 197–203. https://doi.org/10.1080/00405840802153940

McCabe, D. L., Butterfield, K. D., & Treviño, L. K. (2012). *Cheating in college: Why students do it and what educators can do about it*. Johns Hopkins University Press.

McCabe, D. L., Treviño, L. K., & Butterfield, K. D. (2001). Cheating in academic institutions: A decade of research. *Ethics & Behavior, 11*(3), 219–232. https://doi.org/10.1207/S15327019EB1103_2

Murdock, T. B., & Anderman, E. M. (2006). Motivational perspectives on student cheating: Toward an integrated model of academic dishonesty. *Educational Psychologist, 41*(3), 129–145. https://doi.org/10.1207/s15326985ep4103_1

Newton, P. M. (2018). How common is commercial contract cheating in higher education and is it increasing? A systematic review. *Frontiers in Education, 3*, Article 67. https://doi.org/10.3389/feduc.2018.00067

Nowell, L. S., Norris, J. M., White, D. E., & Moules, N. J. (2017). Thematic analysis: Striving to meet the trustworthiness criteria. *International Journal of Qualitative Methods, 16*(1), 1–13. https://doi.org/10.1177/1609406917733847

OECD. (2023). *PISA 2022 results (Volume I): The state of learning and equity in education*. OECD Publishing. https://doi.org/10.1787/53f23881-en

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, Article n71. https://doi.org/10.1136/bmj.n71

Park, C. (2003). In other (people's) words: Plagiarism by university students—Literature and lessons. *Assessment & Evaluation in Higher Education, 28*(5), 471–488. https://doi.org/10.1080/02602930301677

Park, N., & Lee, H. (2012). Social implications of smartphone use: Korean college students' smartphone use and psychological well-being. *Cyberpsychology, Behavior, and Social Networking, 15*(9), 491–497. https://doi.org/10.1089/cyber.2011.0580

Perkins, M. (2023). Academic integrity considerations of AI large language models in the post-pandemic era: ChatGPT and beyond. *Journal of University Teaching & Learning Practice, 20*(2), Article 07. https://doi.org/10.53761/1.20.02.07

Rest, J. R. (1986). *Moral development: Advances in research and theory*. Praeger.

Rudolph, J., Tan, S., & Tan, S. (2023). ChatGPT: Bullshit spewer or the end of traditional assessments in higher education? *Journal of Applied Learning & Teaching, 6*(1), 342–363. https://doi.org/10.37074/jalt.2023.6.1.9

Seo, K., Tang, J., Roll, I., Fels, S., & Yoon, D. (2021). The impact of artificial intelligence on learner–instructor interaction in online learning. *International Journal of Educational Technology in Higher Education, 18*, Article 54. https://doi.org/10.1186/s41239-021-00292-9

Seth, M. J. (2002). *Education fever: Society, politics, and the pursuit of schooling in South Korea*. University of Hawai'i Press.

Silver, L. (2019, February 5). *Smartphone ownership is growing rapidly around the world, but not always equally*. Pew Research Center.

https://www.pewresearch.org/global/2019/02/05/smartphone-ownership-is-growing-rapidly-around-the-world-but-not-always-equally/

Stokel-Walker, C. (2022). AI bot ChatGPT writes smart essays—Should professors worry? *Nature*. https://doi.org/10.1038/d41586-022-04397-7

Sullivan, M., Kelly, A., & McLaughlin, P. (2023). ChatGPT in higher education: Considerations for academic integrity and student learning. *Journal of Applied Learning & Teaching, 6*(1), 31–40. https://doi.org/10.37074/jalt.2023.6.1.17

Thomas, J., & Harden, A. (2008). Methods for the thematic synthesis of qualitative research in systematic reviews. *BMC Medical Research Methodology, 8*, Article 45. https://doi.org/10.1186/1471-2288-8-45

Tong, A., Sainsbury, P., & Craig, J. (2007). Consolidated criteria for reporting qualitative research (COREQ): A 32-item checklist for interviews and focus groups. *International Journal for Quality in Health Care, 19*(6), 349–357. https://doi.org/10.1093/intqhc/mzm042

Weber-Wulff, D., Anohina-Naumeca, A., Bjelobaba, S., Foltýnek, T., Guerrero-Dib, J., Popoola, O., et al. (2023). Testing of detection tools for AI-generated text. *International Journal for Educational Integrity, 19*, Article 26. https://doi.org/10.1007/s40979-023-00146-z

Whitley, B. E. (1998). Factors associated with cheating among college students: A review. *Research in Higher Education, 39*(3), 235–274. https://doi.org/10.1023/A:1018724900565

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—Where are the educators? *International Journal of Educational Technology in Higher Education, 16*, Article 39. https://doi.org/10.1186/s41239-019-0171-0