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AI-Based Digital Cheating At University, and the Case for New Ethical Pedagogies

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Abstract

The proliferation of generative artificial intelligence challenges the credibility of assessment in higher education. This article advances a theoretical argument that universities must move beyond detection-based strategies towards ethically grounded, validity-driven assessment practices. Drawing on Ajzen's Theory of Planned Behaviour, Bandura's Self-Efficacy Theory, and situational crime prevention models, it analyses how AI exacerbates existing vulnerabilities within massified, commodified education systems. Technical countermeasures, including digital proctoring systems, are critically evaluated and found insufficient as standalone solutions. The case of Baird and Clare is used to illustrate how rehumanised, collaborative assessments can mitigate misconduct by enhancing student agency and ethical engagement. The article argues that safeguarding academic integrity in an AI-saturated era demands a fundamental pedagogical realignment, restoring the intrinsic purposes of higher education and resisting the instrumental rationalities that underpin surveillance-based governance.

Keywords Generative artificial intelligence · higher education · cheating · academic integrity · assessment · ethical pedagogy

The rapid advancement of generative artificial intelligence (AI) has destabilised fundamental assumptions about the assessment of knowledge within higher education. Systems such as ChatGPT, Claude, and Gemini, based upon Large Language Models (LLMs), can now produce outputs that closely mimic authentic student work. If universities cannot reliably distinguish between machine-generated and human-authored assessments, the credibility of academic credentials, and the trust underpinning them, is placed in jeopardy.

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Prevailing institutional responses have largely centred upon the enhancement of technological surveillance, including AI detection systems and online proctoring tools. However, such strategies are inherently limited. The sophistication of AI renders detection increasingly unreliable, and a governance model predicated upon suspicion risks deepening the alienation between students and their institutions. Reliance on technological policing via tools such as Turnitin, PlagScan, Safe Exam Browser and Urkund reflects a wider technocratic rationality within the academy, in which student agency is supplanted by regimes of compliance and audit.

This article argues that a more fundamental pedagogical realignment is required. Preserving academic integrity in the AI era demands not merely new detection technologies but a rethinking of the purposes and structures of assessment themselves. Drawing upon Ajzen's (1991) Theory of Planned Behaviour, Bandura's (1977) Self-Efficacy Theory, and situational crime prevention models (Clarke, 2017), it contends that rehumanised, validity-driven assessment designs that cultivate ethical agency are the only sustainable path forward.

This article therefore addresses two key questions:

To what extent do current university assessment practices contribute to the conditions under which AI-facilitated academic misconduct flourishes?

How might validity-based, ethically oriented pedagogical strategies mitigate the risks posed by generative AI?

The discussion is grounded through the illustrative case of Baird and Clare's (2017) application of situational crime prevention principles to assessment design, which demonstrates that misconduct can be substantially reduced not by intensifying surveillance, but by structurally embedding deterrents within supportive learning environments. Their case suggests that assessment environments that emphasise authenticity, personalisation, and iterative engagement reduce both the temptation and feasibility of academic dishonesty.

More broadly, the article situates AI-assisted cheating within the context of the massification and commodification of higher education. As Ashwin (2024) and Tomlinson and Watermeyer (2020) have argued, the reframing of education as a transaction for credentials rather than as a process of intellectual formation has weakened intrinsic student engagement and fostered instrumental attitudes towards learning. When education becomes merely a mechanism for employment credentialing, and assessments are experienced as bureaucratic hurdles, students are more likely to adopt ethically disengaged approaches to performance.

Thus, AI does not *create* the crisis of academic integrity; it exacerbates *existing structural vulnerabilities* within the contemporary higher education system. Massified, depersonalised, standardised assessment regimes, designed for administrative convenience rather than pedagogical fidelity, are especially susceptible. The failure of detection-based solutions is therefore not a technological failure alone, but a symptom of deeper systemic pathologies.

In order to uncover potential remedies, the article examines in greater depth the behavioural theories relevant to understanding student misconduct, analyses the technical affordances of AI in facilitating cheating, critiques the limits of detection-based responses, and articulates a model of validity-driven assessment grounded in the cultivation of ethical student agency. In doing so, it proposes that safeguarding academic integrity in an AI-saturated future requires universities to rediscover their ethical and educational missions as sites of critical, transformative learning rather than credentialing factories.

To fully comprehend the vulnerabilities exposed by AI within assessment practices, it is necessary first to examine the historical evolution of assessment itself, and the structural pressures that have progressively undermined its validity. The next section therefore situates the present crisis within the longer arc of massification, commodification, and depersonalisation in higher education.

The Problem of Assessment in Universities

The need for assessment change within universities is not new. From medieval Latin disputations (debates) to hand-written examinations and, more recently, high-stakes online testing, universities have consistently varied their assessment formats in response to internal and external stimuli (Byrd, 2001). Within this adaptation, the credibility of any university assessment lies in its integrity (by integrity we mean here the reliability and validity of that assessment in the wider societal context). However, this integrity is now under increased threat due to artificial intelligence tools developing the ability to emulate human language much more accurately. Generative AI can answer questions and construct assignments that closely resemble human responses, and can be added to the list of existing 'e-cheating' methods available to students (listed in Dawson, 2020, just prior to the advent of generative AI) alongside more productive uses of the technology. Even if educational institutions were somehow to be shielded from these systems, open-source systems with similar capabilities exist, allowing those with relevant technical skills to create systems for noble or malicious use. This raises inevitable questions about how assessors can differentiate real from fake, a problem facing Education Committees across the university sector. Indeed, some recent studies suggest that AI-generated text can pass as human-authored in up to 80% of cases, making reliable differentiation a significant challenge (Cotton et al., 2023; Eke, 2023; Elkhatat et al., 2023; Liu et al., 2024). If universities cannot differentiate between digital and human responses, they risk accusations of awarding degrees earned via AI algorithms rather than through student effort. Should this become universal, the credentialised higher education (HE) model as we know it faces the risk of collapse without appropriate anticipation of any useful alternative.

This risk stems from the rise in plagiarism at universities generally, certainly since the 1930s, when research compared honour and proctor systems in one university (Campbell, 1935), and in the 1960s, when the first major academic study of cheating at university was carried out (Bowers, 1964). Studies estimating cheating levels are for fairly obvious reasons difficult to conduct, as Dawson (2020) explains, often relatively unreliable, vary in design, and at best rely on self-reported data. By the mid-2000s, as many as 80–90% of students were likely to have cheated at both secondary school and university according to Murdock and Anderman (2006), although consensus on exact numbers remains elusive (Dawson, 2020). Early cheating at university involved using 'crib notes', copying from books, or copying another student's work, as noted in the Cornell Value Study (Goldsen et al., 1960). Cheating now takes a range of forms across social and individualistic cheating, using new technologies as they become available, ranging from smart watches and calculators to online essay mills, and beyond (Bennett, 2005; Bucciol et al., 2020; Dawson, 2020; Krienert et al., 2021). This diversity of cheating methods demonstrates the necessity of clearly distinguishing between types of AI technologies and their implications. For instance, LLMs differ significantly from generative AI systems trained on visual or multimodal data, which creates nuanced challenges in detecting and addressing misconduct. It is even difficult to establish a reliable definition of what constitutes 'cheating' given some university systems internationally (for example in Africa) rely more on memorisation and reproduction of knowledge, whereas others (for example in Europe) require critical interpretation and a great degree of originality enabled through student-centred teaching and learning (Wanyama Wanyonyi, 2024).

At the heart of the problem for universities is a growing divide between students primarily interested in gaining knowledge and those focused on acquiring credentials (tendencies which can exist within the same student at different times (see Hosny & Fatima, 2014). This can often be influenced heavily by the spread of human capital theory, which potentially results in relationships with knowledge becoming commoditised and distorted (Ashwin, 2024). This lies in contrast to real engagement with what McArthur describes as the 'complex, contested and dynamic' knowledge necessary for HE to play a full and productive role within society (McArthur, 2013). This tendency is amplified by increasingly depersonalised assessment processes (Naidoo & Jamieson, 2005). Standardised assessments, submitted anonymously and marked by assistants who may not know the students, are common. While this approach focuses on consistency, representing a pragmatic response to higher education massification, it also creates the conditions for misconduct, especially in a marketised system that may be losing a sense of its core pedagogical purpose (Love, 2008).

Universities' quality assurance protocols often require unrealistically high levels of forensic evidence to prove cheating, detering staff from pursuing investigations (Brigham & Ziebart, 2020; Keith-Spiegel et al., 1998). Yet, if instructors do not address cheating, then it is likely to proliferate (Packalen & Rowbotham, 2022). The costs of this problem are growing as AI-based detection tools that are sufficiently nuanced are difficult to provide and often inconsistent, setting up tensions between lecturers and students (Alexander et al., 2023; Chaka, 2023; Elkhatat et al., 2023; Ibrahim, 2023; Walters, 2023; Weber-Wulff et al., 2023). At the same time, competition amongst contract cheating providers (from essay mills where assignments can be commissioned to entirely digitalised processes using Large Language Models) has significantly reduced cheating costs, taking place within what has been termed the 'gig academy' (Gauman & Veale, 2024; Kezar et al., 2019; Sweeney, 2023). This means that digital cheating has become a war of attrition between lecturers and students (Keir & Ives, 2022), one that lecturers cannot hope to win just by allocating more time and resources to detection as class numbers grow and universities seek further efficiencies. For example Gaumann and Veale (2024) note that contract cheating platforms have begun incorporating AI to automate client communication, further lower barriers to misuse. New insights and approaches to prevention are needed. Here, universities could draw from lessons learned during the rapid shift to remote teaching during COVID-19, which highlighted the importance of adapting assessments to support student agency and equity. This might include integrating collaborative and process-orientated assessments. Insights from remote teaching during the pandemic also demonstrate the efficacy of low-stakes, iterative assessments in fostering student engagement and reducing opportunities for misconduct (Surahman & Wang, 2022). For example, weekly collaborative assignments in online learning environments were found to increase intrinsic motivation and student ownership of the learning process, providing a valuable framework for future assessment design. This approach emphasises authentic, real-world tasks that challenge students to engage deeply with subject material whilst reflecting their individual learning processes. By designing assessments that incorporate these elements, lecturers can reduce opportunities for cheating and encourage genuine intellectual growth.

Having established how structural transformations have eroded the integrity of assessment, it is critical to explore the behavioural mechanisms underpinning student decisions to engage in misconduct. The following section applies psychological models to illuminate the motivational dynamics driving academic dishonesty.

Cheating as a Planned Behaviour: Control, Motivation, and Behavioural Models

Understanding student cheating requires examining behavioural models as well as the impact of evolving technologies on academic dishonesty. The decision to cheat is intricately linked to student motivation and influenced by the need for self-determination and perceived control. Bandura (1977) and Ryan and Deci (2017) argue that students' self-determination needs significantly impact their learning engagement and their motivation, making it central to understanding academic dishonesty. The literature identifies two main loci of control: an external locus, which is linked to academic dishonesty (Leming, 1980), and an internal locus of control by the individual, which is linked to academic honesty (Rinn et al., 2014). When students feel a lack of agency and control, the perceived barriers to cheating decrease, increasing their motivation to cheat.

Murdock and Anderman (2006) demonstrate an integrated model of such academic dishonesty that frames cheating around three motivational questions: (1) "What is my purpose?" (concerning extrinsic goals and performance orientation); (2) "Can I do this?" (self-efficacy and outcome expectations); and (3) "What are the costs?" (prospects of punishment and self-image). Their model suggests that extrinsic goals, which focus on external rewards rather than the intrinsic enjoyment of learning, are more strongly associated with cheating. Students motivated by external pressures and competition for grades are likelier to cheat. Conversely, a mastery-oriented classroom that values intrinsic goals and supports self-efficacy reduces the likelihood of cheating.

Ahsan et al. (2021), found in a systematic review of contract cheating that difficulties with time management, struggles with academic performance, personal issues, and university-related pressures (such as overly challenging or poorly explained assignments, assessments that feel disconnected from the student's experience or understanding, high-stakes tests, and tight or conflicting deadlines) can all contribute to academic misconduct. When students have limited engagement with formative assessment processes that provide constructive feedback, the pressure to cheat intensifies.

In their meta-analysis, Krou et al. (2021) found that, while self-efficacy negatively correlates with cheating, actual ability does not inversely correlate with dishonesty. In other words, being a higher-ability student does not necessarily mean you are less likely to cheat. Students with high self-belief might cheat if they perceive assessments as unfair, using cheating as a strategy to regain control and self-determination. The rise of generative AI complicates this dynamic by reducing the traditional costs of cheating, such as time and effort, and making detection more complex, which may even be culturally specific (Yusuf et al., 2024).

While an understanding of planned behaviour offers important insights, a broader theoretical landscape must be considered to appreciate the multifactorial nature of cheating. The next section evaluates competing criminological and psychological theories, assessing their explanatory power in the context of AI-facilitated misconduct.

Cheating and Behavioural Theory: Theoretical Models and their Explanatory Power

Looking at different theoretical models of behaviour can offer deeper insight into cheating. For example Ajzen's **Theory of Planned Behaviour** (TPB) (1991) sheds light on the decision-making process in cheating by focusing on attitudes, subjective norms, and perceived behavioural control. TPB suggests that behaviour is shaped by an individual's attitude toward it, perceived social norms (subjective norms), and their belief in how easy or difficult cheating is (perceived behavioural control). Regarding academic dishonesty, TPB is useful to us in explaining how students' attitudes towards cheating, peer influence, and perceived ability to avoid detection potentially contribute to their decisions to cheat.

Bandura's **Self-Efficacy Theory** (1977) complements Ajzen's TPB by focusing on students' confidence in their academic abilities, at an individual level. Although it does not factor in variables in the external environment, or deals specifically with cheating, it does allow us insight into some thought processes that may underpin the decision to cheat. It does this by explaining how beliefs about competence affect a sense of perceived control. Bandura's theory show us how this belief can shape whether students see cheating as necessary to meet their goals, and how capable they might feel using AI tools to avoid detection. Combining these theories, TPB explores broader influences such as attitudes and social norms, while Self-Efficacy Theory explores personal confidence.[1] Understanding both is particularly relevant in terms of AI, where advanced tools make cheating even easier and harder to detect. A student confident in the use of AI tools might see less risk of getting caught, increasing the likelihood of dishonesty. This combined theoretical approach also shows that a key aspect of cheating is the interaction between technology's ease of misuse and the individual factors that influence students' choices, offering a nuanced understanding of academic dishonesty in the AI era (if we are to call it that).

Other theories are available, but perhaps offer fewer insights. For example, Agnew and Briezina's (2019) **General Strain Theory** and Sykes and Matza's (1957) **Neutralisation Theory**, which address how strain or rationalisation can lead to deviant behaviour, are less applicable because they focus specifically on crime. These theories are typically used to analyse high personal or emotional strain, beyond what most university students face, whereas AI reduces barriers to cheating without causing such strain. Similarly, **Routine Activity Theory** (Cohen & Felson, 1998) and **Social Learning Theory** (Bandura, 1977) may not fully capture the individual decision-making processes central to AI cheating scenarios, though the latter could help address social pressures (or trends) related to cheating. In the next section, we explore individual motivation to cheat in more depth.

If cheating arises from the interaction of motivational, cognitive, and social factors, then prevention strategies must engage with these domains holistically. The next section therefore outlines how fostering positive motivational states and ethical self-concepts among students can reduce the propensity to cheat.

[1] For reasons of space we have not explored and theorised individual external-to-the-student factors such as variable quality of tuition, poor learning environment and so on as potentially mitigating elements surrounding academic cheating, although these would be valid avenues as well.

Negating Cheating through Positive Social and Motivational Self-Concepts

One way of understanding AI-based cheating (of several) is as a planned behaviour likely to be rooted in a belief system that suggests a student can get away with it, and that is the approach we are taking in this article. This means that simply banning technologies that assist cheating is neither a simple nor sufficient solution, as it does not deal with the problem at source (Leaton Gray & Phippen, 2017; Parapadakis, 2004). Therefore, efforts to reduce cheating should focus on enhancing the perceived purpose of assessments, fostering self-efficacy in a broad sense, and increasing the perceived costs of cheating (Krou et al., 2021; De Maio & Dixon, 2022). Any approach focusing solely on only one or two of these areas will likely fail, as it needs all three to be complete. A holistic and adaptive model based on these factors, considering the dynamic nature of planned behaviour, is necessary for universities and society to thrive alongside AI. Dawson et al. (2024) validity framework is particularly relevant here, as it provides a structured approach to align assessments with intrinsic motivation and self-efficacy. This framework emphasises authentic, real-world tasks that challenge students to engage deeply with subject material while reflecting their individual learning processes. By designing assessments that incorporate these elements, educators can reduce opportunities for cheating and encourage genuine intellectual growth.

Table 1 illustrates five discipline-specific indicative examples of this form of assessment, designed to reduce cheating by emphasising intrinsic motivation and self-efficacy.

Changes such as these are important because De Maio and Dixon (2022) argue that promoting academic integrity requires a systemic approach that aligns assessment design with educational purpose. They highlight how institutions can operationalise this by embedding authentic assessment practices that foster critical thinking, creativity, and the application of knowledge to real-world problems. Linking to Dawson et al. (2024) validity framework is helpful here.

Such practices have been shown to reduce opportunities for academic misconduct and enhance student engagement (Bretag et al., 2019). They do this by helping universities navigate the challenges posed by increasing student instrumentalism (Muddiman, 2018; Wong, 2022). They also help offset the rise of credentialism (Tomlinson & Watermeyer, 2020), where many students are extrinsically motivated by the credentials provided by summative assessments, seen and/or used as a proxy for employability. At a broader level, formative assessment can therefore be seen as an important step in remediating the more negative aspects of university massification, as far as educational quality is concerned (Giannakis & Bullivant, 2015). Improving the perceived purpose of an assessment in this way includes enhancing fairness and encouraging student ownership. This is because promoting a mastery-oriented learning environment that fosters ownership of the assessment process is more likely to reduce cheating. Students who find intrinsic value in learning, such as through personalised assignments that focus on an area of interest, are more inclined to value the assessment of that learning.

Encouraging self-efficacy should have a positive impact (Krou et al., 2021). However, as discussed, self-efficacy can play a role in planning to cheat and deciding not to. It can be linked to youth pessimism and optimism (Keating & Melis, 2022), influencing long-term educational outcomes and employment. Therefore, it is necessary to support the development of positive self-efficacy within the wider university environment. This requires universities to emphasise ethical positioning and clearly define their societal role in the face of the increasing availability of AI. As AI becomes harder

Table 1 Examples of Discipline-Specific Assessment Redesigns

Discipline	Traditional Assessment	Revised Valid Assessment	Practical Implementation Example
STEM	Timed problem-solving exams	Open-book problem-solving with reflective analysis	A physics exam held in a classroom where students solve problems and submit a written reflection on their problem-solving process
Humanities	Summative essay submissions	Collaborative research projects involving primary and secondary sources	A history course requiring groups to create a digital exhibit, incorporating archival research and team-based analysis
Business	Case study analysis	Real-world simulations with peer-reviewed presentations	A business module that includes a simulated market strategy development, with students pitching to a panel of peers and instructors
Social Sciences	Theoretical essays	Community-based action research	A sociology assignment where students partner with local organisations to design and evaluate social impact interventions
Creative Arts	Portfolio submissions	Iterative peer-reviewed design processes	A design course requiring students to develop a project across multiple stages, incorporating iterative feedback from peers and industry professionals

to detect and potentially nefarious (Ferrara, 2024), universities need to articulate their ethical stance much more clearly and obviously (well beyond a section in the student handbook) to mitigate AI's negative impacts.

The reason is that, while AI reduces the costs of cheating related to time, effort, and money, it has minimal impact on the social costs of cheating, such as public humiliation and ostracism. Penalties for using AI to cheat are usually equivalent to those for traditional methods if detected by a lecturer or administrator, or via human review of a software alert. However, if students value their self-image as part of an intellectual community that rejects cheating for intellectual and ethical reasons, it could discourage AI-based cheating in the first place. This is because when students develop strong self-identities, they are less likely to plan to cheat, particularly in depersonalised educational settings with significant extrinsic pressures (Ajzen, 1991, 2005). Promoting these desired ethical norms aligned with students' ideal future selves can also reduce the chances that critical attitudes towards cheating will override enabling attitudes. This is because a student's ideal future self represents an aspirational identity (Boyatzis & Akrivou, 2006), which drives their identity development at university.

However, this is difficult in practice, as the hidden curriculum of the contemporary university, with a growing focus on individualism, may inadvertently promote cheating as a shortcut for an individual under pressure. Contributing to this may also be the uncritical excitement, if not outright moral panic, surrounding AI in higher education leadership and policy. This amounts to a kind of management eschatology, focusing on 'end-of-world' scenarios, at least for contemporary universities and careers. It suggests that some kind of AI takeover of society is all but unavoidable and may compromise future jobs unless students master AI intellectually and practically. In such an existentially challenged environment, it is unsurprising that some students see AI as a tool for surviving university life. If we can't beat our future AI overlords, the logic of this argument goes, we may as well join them by mastering the technology ourselves. Gallent-Torres et al. (2023) argue for this as a life skill when debating the two sides of the problem – defeatism or resistance to change versus embracing opportunities.

While motivational interventions are critical, the technical dimensions of AI-enabled misconduct present distinct challenges that must also be understood. The following section examines how Large Language Models facilitate both asynchronous and synchronous cheating, and the limits of current detection mechanisms.

Asynchronous and Synchronous Cheating with LLM-based sytems: Technical Perspectives

As we have argued, the advent of advanced AI tools, particularly Large Language Models (LLMs), presents significant challenges for detecting and addressing academic dishonesty in higher education. Understanding these technical challenges is crucial for developing effective strategies to uphold academic integrity that fit holistically within a more student-focused university environment. Below, we explore the key issues associated with asynchronous text generation, paraphrasing and plagiarism evasion, synchronous cheating during online exams, and the potential use of hidden codes.

Definition of an LLM

LLMs, based on a Transformer model proposed in 2017 (Vaswani et al., 2017), generate coherent and contextually relevant text from input prompts by converting text into numerical tokens and processing these through a network to predict and generate responses. For example, a student might use an LLM-based tool to produce an essay by inputting a prompt related to their assignment. While these models are not genuinely intelligent, because they rely on patterns in existing data rather than understanding content, their ability to produce well-written, contextually appropriate text makes them a tempting tool for students seeking to fulfil assignment requirements with minimal effort.

Paraphrasing and Plagiarism Evasion

Transformers excel at paraphrasing and can easily bypass conventional plagiarism detection supporting systems. These systems typically compare submitted work against a database of previously published texts to identify similarities. However, because Transformers generate original content rather than copying from existing texts, the output often does not match anything in the detection database. Additionally, Transformers can rephrase content while preserving its original meaning, which makes it challenging for plagiarism detectors to identify such content as copied. Studies show that these tools have only a marginally higher success rate than human reviewers, with detection rates around 80% for machines compared to 78.4% for humans (Wahle et al., 2022). This adaptability of Transformers further complicates efforts to catch plagiarism.

Synchronous Cheating During Online Examinations

Although research into this area is at a relatively early stage, and evidence is not yet definitive, it is clear that students can be extremely innovative in findings ways to cheat in examinations (Odongo et al., 2021). For example students might use AI-powered tools to cheat in real-time (e.g. Kucukgocmen, 2024). They might copy exam questions, input them into an AI tool, and receive answers instantly. Many digital proctoring systems therefore aim to ensure exam integrity by monitoring the exam environment. However, these systems often rely on static surveillance and basic liveness tests that can be bypassed. Additionally, the reliance on digital proctoring can sometimes create a stressful environment that assumes students are potential cheaters rather than active learners (Lee & Fanguy, 2022). As a consequence, proctoring software can be seen as invasive by students, and even a legitimate target for subversion (Simko et al., 2024).

Injecting Hidden Codes

An innovative approach to counter AI-driven cheating involves embedding hidden codes or metadata into AI-generated text. This technique, inspired by methods used in computer gaming, adds invisible markers to the text that can signal its AI origin to detection tools. For instance, a custom function could add HTML comments (‘remarks’) such as < ---- !> to the text that are detectable by specialised tools (in other words, a form of watermarking, see Wang et al., 2024). However, the effectiveness of this approach depends on the student's diligence in modifying the text and ensuring that hidden codes are not easily removed or overlooked. It would also require that existing LLMs also deploy such watermarking, based on a confidential proprietorial algorithm, to avoid disruption to the process. This could be quite robust if used universally, but would easily be circumvented by, for example, simply retyping text manually.

The technical aspects of AI-driven cheating therefore present significant challenges for detection. By understanding the mechanisms of asynchronous text generation, the limitations of plagiarism detection supporting systems, the nuances of synchronous cheating during online exams, and the potential limitations of hidden codes in software universities might be involved in commissioning in the future, lecturers can better address the evolving landscape of academic dishonesty. A further step would involve contextualising these assessments to account for issues such as digital divides (such as subsidised high speed Internet and devices) and social contexts (such as quality of accommodation, caring responsibilities and so on), recognising that equitable access to resources remains a fundamental barrier to academic integrity. In addition, a rehumanised approach to assessments, such as interactive viva-style examinations or peer-mediated assessments, could foster engagement and reduce reliance on AI tools. The next section therefore shifts focus towards pedagogical reform, exploring how rehumanised, personalised assessment practices can disrupt the conditions that enable misconduct.

Reversing the Cheating Trend

Cheating is a deliberate, planned behaviour (Ajzen, 1991, 2005), and evolving social norms in higher education shape students' attitudes toward it. Students' perceptions of cheating may offer more insight into its prevalence than the perspectives of academic staff, and two related questions need to be addressed. The first key question for universities to consider is whether cheating is socially unacceptable to the extent that it effectively deters their students. Evidence suggests that it does not generally evoke strong moral outrage. Surprisingly for us (as we were sufficiently concerned as to author an article), cheating is not seen as inherently immoral by many students (Ashworth et al., 1997; Krou et al., 2021; Marsden et al., 2005), and similar attitudes can even be found amongst academics (Godecharle et al., 2018; Martinson et al., 2005), higher education institutions (ICAC, 2005), and society at large (Henle et al., 2019; Wood et al., 2007). While this does not prove that cheating is universally accepted, it does indicate that students who choose to cheat may interact with peers who view a degree of academic dishonesty as acceptable, a group Eisenberg describes as 'amorally oriented', see Eisenberg, 2004). As a result, these students are unlikely to perceive a significant social cost such as shame or humiliation, even if their cheating is detected.

The second key question is: if cheating is increasing and technological advances like AI are not the primary cause, what are its drivers? To answer this, we must examine what the involvement of AI in cheating reveals about the nature of assessment itself. If AI can meet assessment outcomes and convince assessors, it suggests that current assessments may not effectively measure intellectual or knowledge-based achievement. AI can perform tasks such as sourcing relevant information, compiling it into a coherent narrative, and paraphrasing without understanding the subject matter, which are far from the competencies that valid assessments should evaluate. If the contribution of AI to cheating is intellectually trivial, then an assessment that can be answered by AI in a way that deceives an assessor is an assessment whose answer is intellectually trivial. The assessment is, therefore, failing in its fundamental purpose. It does not measure whether students have achieved the necessary level of knowledge and ability but rather whether they, or anyone with no subject knowledge, can identify keywords, compile information, and paraphrase it. This issue precedes AI; the technology has simply exposed the superficiality of such assessments (Blackie, 2024; Kramm & McKenna, 2023).

The drive towards scaling, standardising, and depersonalising assessments has been pursued for years, often to increase access to higher education (Stray, 2001) and reduce perceived bias as well as increasing assessment reliability and validity. However, noble aims do not necessarily lead to beneficial outcomes (Leaton Gray, 2018; Pitt & Winstone, 2018). These standardisations often conflict with the principles of effective learning. For example, Bennett and Burke (2017) deconstruct hegemonic conceptions of time in higher education, highlighting the social exclusivity of such a framing. The idea that most subject areas can be taught in the same hours,[2] divided into uniform modules, and assessed with the same amount of work irrespective of discipline, background, or prior experience, serves institutional convenience but defies educational logic and learning theory.

Recognising the pedagogical weaknesses exposed by AI also invites reconsideration of criminological approaches to misconduct. The following section investigates how crime prevention models, particularly situational strategies, can inform more effective assessment designs.

Exploring Criminological Aspects of Cheating: From Punishment to Prevention

Higher education institutions have often adopted criminology-based approaches (often labelled 'catch and punish' systems) to address student cheating, mainly contract cheating, framing misconduct within a criminal justice paradigm (both within the academy and increasing in draft legislation). An alternative method primarily focuses on crime prevention techniques, as seen in Baird and Clare's case study of an Australian university, where 25 situational crime prevention techniques developed by Clarke (2017) were adapted for university use, targeting opportunities for misconduct by increasing the effort required to cheat, raising the associated risks, reducing the rewards, decreasing provocations, and removing excuses. This multifaceted approach reportedly reduced academic misconduct cases from 183 to 27 within a year and is worth further examination. It does not relate directly to AI and specifically LLM-use, but it does provide a useful framework for thinking through the social and pedagogical issues that apply in those cases.

In Baird and Clare's case, a computer-based business simulation tracked and monitored students' interactions. Tools like a red-flag system (detecting discrepancies and/or overly expert work) and the random reassignment of team members (board shake-up) were employed to increase the effort and risks of cheating, adding the kind of friction to cheating that is often missing in current educational settings. In this sense, there was an element of 'catch and punish' but also a keen interest in helping students to be in a position where unethical behaviour was not felt by them to be necessary or practicable. Students were given easily digestible

[2] For example, at the UCL Institute of Education, where two of us work, each 30 Master's level credit module is said to require 300 nominal learning hours.

information regarding academic misconduct, which laid out behaviour standards, removing excuses for cheating and, as the authors describe it, ‘priming a student’s conscience’. Some of the course materials and answers had been published on the Internet by students (in some cases in return for payment), and platforms were formally issued with takedown notices under copyright law. Weekly in-class invigilated tests increased the effort required to cheat but also restored a level of personal oversight and interaction between students and lecturers. Finally, new video case studies were recorded, involving real people involved in leading businesses, to be used once only. This suggests that rehumanising the assessment process by making it more interactive and personalised may be a key factor in enhancing academic integrity.

While these situational crime prevention strategies were well-suited to the specific nature of the business simulation, their effectiveness may not translate to other forms of assessment. The simulation allowed for precise monitoring, but such granular tracking might not apply to more subjective or less structured assessments, such as essays or project-based tasks. The variability introduced between classes, for example, ensured that different market conditions were created for each group, complicating attempts to replicate or outsource the work, but also promoting teamwork and adaptability. While effective in this context, this measure could be difficult or impractical to apply to other types of coursework (especially tightly regulated, accredited courses), suggesting the limits of these crime prevention techniques when applied broadly across different assessment forms.

Nevertheless, there is growing support for this kind of validity-based framework of assessment, as suggested by Dawson et al. (2024), moving away from criminalising student behaviour and focusing on whether assessments genuinely reflect students’ understanding and abilities. From this perspective, the ethical dimension of pedagogy must shift from merely catching cheaters to ensuring that assessments are designed to promote deep learning and reduce the incentive to cheat in the first place (as they say, by reducing temptation and arousal). Baird and Clare’s study indirectly supports this idea by highlighting that certain interventions, such as the introduction of additional learning opportunities like the Simulation Footrace (a non-assessed competition provided so students can practise), helped reduce stress and provided students with the chance to engage more deeply with the simulation, thus removing excuses for cheating.

Overall, their holistic response to the cheating problem provides a good example of an ethical pedagogy devised via the imaginative rethinking of assessment design. The reliance on formulaic and often recycled assessment tasks (seen in the frequent reuse of simulation parameters before introducing more variability) created opportunities for misconduct by making it easier for students to outsource their work or find previous examples to mimic. By investing in bespoke, single-use materials and assessments tailored to specific learning outcomes, it is clear that educators can reduce the incentive to cheat, as students are less likely to find shortcuts that undermine their learning. However, this takes time, something which is frequently in conflict with most contemporary workload models at universities.

The empirical insights drawn from crime prevention models reinforce the need for a broader theoretical and ethical reconfiguration of pedagogy. The final section synthesises these findings, proposing a validity-driven model for assessment and outlining directions for future research.

Towards a New Ethical Model of Pedagogy and Assessment

The advent of generative artificial intelligence necessitates a profound re-evaluation of how academic integrity is conceptualised and safeguarded within higher education. This article has argued that the dominant paradigm of technological detection and surveillance is inadequate. AI has rendered such measures both unreliable and increasingly antagonistic to the educational relationship. Instead, preserving academic integrity requires a fundamental shift towards assessments that are valid, ethical, and human-centred.

Drawing upon theories of planned behaviour and self-efficacy, the article has demonstrated that misconduct is not merely a function of opportunity but of motivation, perceived control, and social norms. In an educational environment that foregrounds extrinsic credentialism over intrinsic learning, and where assessments are depersonalised and instrumentalised, the temptation to engage in misconduct flourishes. AI merely amplifies these tendencies by making misconduct easier, cheaper, and harder to detect. The case study of Baird and Clare (2017) illustrates the potential of structurally re-engineered assessment environments to mitigate cheating not through punitive surveillance, but through the design of tasks that promote genuine engagement, increase the effort and risk associated with dishonesty, and foster ethical norms. Situational crime prevention strategies, adapted to educational settings, highlight the importance of making misconduct not only more difficult but also less desirable and less necessary.

Beyond immediate technical responses, universities must attend to the broader sociological risks posed by the rise of AI. The erosion of trust, the hollowing-out of the student–teacher relationship, and the further commodification of learning threaten to precipitate a legitimation crisis for the academy itself. If assessments no longer meaningfully reflect knowledge, understanding, or ethical development, the social contract between universities and society will be irreparably damaged. The future of academic integrity, therefore, lies not in more sophisticated detection tools, but in the reclamation of education as an intrinsically valuable, ethically significant practice. Validity-driven assessment must be at the core of this reorientation, embedding learning processes that are resistant to the instrumental logic of AI. Institutions must foster environments in which students are not merely subjects of regulation, but active participants in their own intellectual and ethical formation.

Future research must build upon this theoretical framing to empirically explore the effectiveness of validity-based assessment interventions across diverse disciplinary and cultural contexts. Only by embedding integrity within the very fabric of pedagogical practice can higher education sustain its mission in an AI-saturated world.

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