

Review

Generative Artificial Intelligence in Tertiary Education: Assessment Redesign Principles and Considerations

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Abstract: The emergence of generative artificial intelligence (AI) such as ChatGPT has sparked significant assessment concerns within tertiary education. Assessment concerns have largely revolved around academic integrity issues among students, such as plagiarism and cheating. Nonetheless, it is also critical to consider that generative AI models trained on information retrieved from the Internet could produce biased and discriminatory outputs, and hallucination issues in large language models upon which generative AI acts provide made-up and untruthful outputs. This article considers the affordances and challenges of generative AI specific to assessments within tertiary education. It illustrates considerations for assessment redesign with the existence of generative AI and proposes the Against, Avoid and Adopt (AAA) principle to rethink and redesign assessments. It argues that more generative AI tools will emerge exponentially, and hence, engaging in an arms race against generative AI and policing the use of these technologies may not address the fundamental issues in assessments.

Keywords: assessment; generative artificial intelligence; ChatGPT; AAA principle; tertiary education



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1. Introduction

Generative artificial intelligence (AI) has gained enormous attention since the release of ChatGPT in late 2022, given its capability to understand human language and conduct conversations with users using natural language or human-like language. Generative AI has transformed many industries, such as business and healthcare, offering promising applications to enhance their functions and productivity. For example, in the business sector, routine work such as customer service or basic financial assessment can be taken over by generative AI; in healthcare, health advice, education and promotion can be carried out by generative AI [1]. Further, in the creative and design industries, generative AI can assist designers and creative professionals in generating content such as images, graphics and videos, as well as architecture and fashion designs [2].

Within the education landscape and particularly in tertiary education institutions, generative AI has impacted how students learn, how teachers teach [3–6] and how assessments are conducted [6]. For instance, given access, students can now use ChatGPT or something similar to generate essays, reports, academic and scientific research papers, programming codes and creative content. While generative AI demonstrates impressive capabilities in tertiary education for learning and teaching, a key concern in most tertiary educational institutions is the potential risk of students using these generative AI tools to cheat and plagiarise their assignments or assessments [7]. Notably, the world's 50 top-ranking tertiary education institutions have developed and published policies and guidelines to guide both students and teachers on academic integrity issues such as plagiarism, acknowledgement of generative AI, detection of generative AI use and assessment design [7]. While it seems possible to use generative AI detection tools such as Turnitin AI, ZeroGPT and GPTZero

to detect AI-generated outputs, concerns such as inaccuracy in AI-generated content or false alarms and ethical and privacy concerns, as well as trust issues between students and instructors, remain critical [7]. To this end, AI detectors are not tenable solutions to concerns with generative AI in tertiary education; it is also impractical to ban generative AI in assessments since students should be prepared for the future of work and life, which will probably require them to use generative AI.

Current discussions and investigations into tertiary education tend to focus on the feasibility of banning or embracing generative AI in developing cognate policies and guidelines. Also, there remains a dearth of research examining the reasons why students use generative AI in the ways they are not supposed to for their assignments. More importantly, the emergence of generative AI has provided opportunities for tertiary educational institutions to rethink and redesign assessments in a way that is fit-for-purpose. Following this line of argument, this conceptual paper proposes key principles and considerations guiding assessment redesign in the era of generative AI by understanding the affordances and risks of generative AI in educational assessments and the issues surrounding academic integrity with generative AI.

2. Affordances and Risks of Generative AI in Educational Assessments

The potential affordances of generative AI tools in education and assessment have been widely investigated since 2023. In a review conducted by Wang et al. [5], four clusters of affordances of generative AI in education were identified. These include (1) accessibility: the capability of generative AI to provide timely help and its accessibility for remote learning; (2) personalisation: to provide students with personalised learning recommendations; (3) automation: to generate ideas, drafts and instructional materials based on human-provided prompts with speedy performance and well-structured responses; and (4) interactivity: to act as an interlocutor for the development of conversational skills, either in written or oral form. In relation to the cluster on automation via human-provided prompts by Wang et al. [5], Pack and Maloney [4] demonstrated how they created language learning and teaching materials and assessments using ChatGPT by supplying appropriate prompts to the generative AI. Park and Maloney [4] have shown the potential of generative AI in generating discussion questions, modifying material appropriate for students of different proficiency levels, generating writing samples for comparison, generating handouts with explanations and practice exercises, generating transcripts for listening assessments, creating rubrics and evaluating student writing based on a rubric.

In particular, for educational assessment, Swiecki et al. [6] highlighted some potential ways AI could be used to automate traditional assessment practices, as well as to transform from a discrete to a continuous assessment and from a uniform to an adaptive assessment, thereby making assessment practices more feasible and meaningful in learning. Examples of AI-based assessment techniques include automated assessment construction, AI-assisted peer assessment, writing analytics, tracking student actions to be incorporated into models of performance and learning via stealth assessment, automated scoring and adaptive learning with instant assessment feedback.

What has been discussed so far includes some potential ways generative AI could be useful for learning, teaching and assessment for students, instructors and those involved in assessment development. Despite these, generative AI is not without flaws and limitations. Miao and Holmes [8], authors of the UNESCO guidance for generative AI in education and research, pointed out some challenges and the emerging ethical implications of generative AI in tertiary education. One major issue highlighted was the lack of explainability and transparency in generative AI, specifically that it currently operates like a 'black box', with its processes and how and why the outputs are generated in a certain way being unknown to users.

Wang et al. [5] highlighted five categories of challenges that generative AI could bring to educational assessment. These include academic integrity risk, response errors and bias, overdependence on generative AI, digital divide issues and privacy and security

concerns. Nah et al. [1] also noted similar challenges from generative AI in terms of ethical and technological issues. Common to these two studies is the quality of training data for generative AI models and their associated ethical issues. As generative models are trained on information retrieved from the Internet, biased and discriminatory outputs can be produced. When inappropriate training data are used, harmful content can also be produced [1,5]. Additionally, hallucination issues in large language models in which generative AI provides made-up and untruthful outputs could be critical and dangerous in specific contexts, such as scholarly activities and seeking medical advice [1]. Evidently, within education, overreliance on generative AI may lead to students blindly adopting answers without verification, impeding their problem solving as well as their creative and critical thinking skills [1,5]. Generative AI could also present equity issues as the gap between students with and without access to it widens. A critical question is then whether higher marks should be awarded to students who are highly skilled in using generative AI to produce assessment output as compared to students who do not use generative AI [5]. Data privacy and security are another prominent challenge in educational assessment [1,5]. While it is generally thought that generative AI is efficient and could be applied to marking assignments, these scripts usually contain students' personal data. Additionally, since generative AI appears to be a 'black' box, little is known about its data security protocol and processes.

3. Assessment Redesign: Unpacking Causes of Academic Integrity Problems with Generative AI

Much of the discussion and debate about the emergence of generative AI in tertiary education has been surrounded by concerns about academic integrity. Such concern is evident in a review by Moorhouse et al. [7], who reported the development and publication of policies and guidelines related to academic integrity by the world's 50 top-ranking tertiary institutions. While academic integrity issues are not new and existed even before the emergence of generative AI, it is important to note that only a minority of students would commit academic dishonesty, with the majority wanting to learn and not commit academic dishonesty [9]. In the past, when there was no generative AI, it would require some effort for students to copy the work of someone else or be involved in contract cheating. Of late, it has evidently become significantly less onerous to commit academic dishonesty since generative AI is widely available and accessible, and the detection of AI-generated content is challenging and almost impossible. Despite these challenges, it is critical to unpack issues related to academic integrity impacted by generative AI to provide insights into redesigning assessments that are fit-for-purpose in the context of tertiary education. The following sections discuss some of these issues in relation to students' intentions when using generative AI, assessment purposes, types of assessment outputs and assessment load.

3.1. Students' Intentions in Using Generative AI

The Theory of Planned Behaviour [10,11] can be used to describe students' violations of academic integrity such that the intention to perform a behaviour (i.e., cheating or plagiarism) is determined by their attitudes towards cheating, subjective norms and perceived behavioural control. Intention, as defined by Ajzen [11], refers to "indications of how hard people are willing to try, of how much of an effort they are planning to exert, in order to perform the behaviour" (p. 113). This intention is affected by the extent to which students perceive academic dishonesty as unfavourable behaviour, the normative perception of other people regarding academic dishonesty and the extent to which students perceive academic dishonesty as difficult.

Many researchers have conducted studies related to academic integrity and the Theory of Planned Behaviour (e.g., [12–16]). What has been commonly found is that students' perceived attitudes towards academic integrity, subjective norms and perceived behavioural control significantly and positively predict their intentions to cheat or plagiarise their

assignments. In other words, when students perceive academic dishonesty as unfavourable and difficult and the norm is that academic dishonesty is unacceptable, students tend not to commit cheating or plagiarism. Through the lens of the Theory of Planned Behaviour, Ivanov et al. [17] conducted a study to examine factors driving the adoption of generative AI in tertiary education. The findings show that the perceived strengths and benefits of generative AI positively impact students' attitudes, subjective norms and perceived behavioural control. In other words, students' perceptions of generative AI as a benefit to their studies shape how they regard academic integrity (i.e., in a positive manner). Through their study, Ivanov et al. [17] demonstrated the possibility of applying the Theory of Planned Behaviour to understand and determine students' violations of academic integrity based on their attitudes towards cheating, subjective norms and perceived behavioural control.

3.2. Purposes of Assessments

Assessment practices in tertiary education serve many different competing purposes. Archer [18], based on the works of Newton [19], Brookhart [20] and Black et al. [21,22], proposed the assessment purpose triangle, which includes *assessment to support learning*, *assessment for accountability* as well as *assessment for certification, progress and transfer*. *Assessment to support learning* typically refers to formative assessment, though summative assessment could also be used to support student learning. This assessment is used to determine student competency levels and identify their learning gaps to better support their learning. As tertiary educational institutions receive funding from the state, they are responsible for providing evidence of student learning to the public and government (i.e., *assessment for accountability*). *Assessment for certification, progress and transfer* is twofold: individual students need certification to endorse their attainment of knowledge and skills for a particular program, while programs and qualifications need to be certified and acknowledged by professional bodies.

It is within expectation that more resources should be provided for *assessment to support learning* since this is the most direct way to strengthen student learning and enable timely remediation to be provided. However, Archer [18] warned against over-emphasising *assessment to support learning*, as this type of assessment typically happens in the classroom and is based on norm referencing, where a comparison of students' performance or progress is carried out at a group level. This could present some negativity, such as an overestimation of some students' skills without considering the standards of other tertiary educational institutions or the standards required by professional bodies. On the other hand, *assessment for accountability* and *assessment for certification, progress and transfer* are "inherently high stakes due to systemic pressures such as institutional funding, accreditation with various bodies, legislative requirements, national and international competition, public and media pressure" [18] (p. 6). This suggests that there could be a situation where resources are invested for these two purposes at the expense of *assessment to support learning*, such that timely improvements and adjustments are less feasible. Thus, the assessment triangle provides some foundations and considerations to help achieve quality education through fit-for-purpose assessment [23]. To this end, consideration of the purpose of assessment is especially important in the era of generative AI, where educators and stakeholders would need to rethink the following: (1) intended program learning outcomes; (2) program-related assessments, whether or not they are still relevant and required; (3) what knowledge or skills need to be retained; and (4) what types of assessment outputs need to be produced.

3.3. Types of Assessment Outputs

A review conducted by Moorhouse et al. [7] showed that there have been many suggestions to redesign assessments in the era of generative AI, including in-person exams or presentations, staged assessments, assessments focusing on progress, assessments incorporating generative AI to identify and critique its limitations and proposed ways to improve AI-generated outputs. However, Lodge et al. [24] highlighted that assessments focusing on the limitations of generative AI tend to ignore the fact that generative AI is an

emerging technology that will eventually improve, and this type of assessment will need to be adjusted or updated. Lodge et al. [24] argued that considering types of assessment outputs for different assessment scenarios is of utmost importance to guide educators towards more sustainable assessment designs for the future.

Additionally, some assessments can be more easily answered or performed by generative AI. These include multiple-choice questions or subjective questions focusing on lower-order skills which assess students' remembering and understanding of certain knowledge, skills or concepts. In situations where these questions are still valid and required for certain assessment purposes, such as certification or accreditation, the corresponding assessment will need to be conducted via in-person exams under invigilation, where students will not be able to use any form of generative AI. Preparing students for the future of work and life is also an important consideration when deciding on a type of assessment output. For example, it would be reasonable for a program or course to have generative AI-integrated assessments if the program expects students to use generative AI tools in their work after graduation.

3.4. Assessment Load

Approaches to measuring assessment load can include weighting between formative and summative assessments, assessment frequency, variations in assessment tasks and assessment deadlines. Tomas and Jessop [25] noted the lack of attention on assessment loads and commented that research evidence has demonstrated that high assessment loads may lead to surface learning, wherein students only learn minimally just to pass a course. Additionally, excessive assessment loads will also increase time pressure for students, and this may lead them to commit cheating or plagiarism. With the wide availability of generative AI, it is even easier for students to engage in academic dishonesty due to high assessment loads.

4. Fit-for-Purpose Assessment: The Against, Avoid and Adopt Principle

The Against, Avoid and Adopt (AAA) principle for redesigning assessments in the context of tertiary education is proposed in response to the changing dynamics and impacts of generative AI on assessment. The AAA principle considers the affordances and limitations of generative AI as well as factors contributing to academic integrity with generative AI. Additionally, the principle proposes that assessment design should reflect the fact that generative AI is an emerging technology and that critiquing the limitations of generative AI as part of assessments may no longer be relevant in the foreseeable future. The principle also reflects a balance in the assessment purpose triangle posited by Archer [18], in that there should not be an over- or underemphasis on certain assessment purposes that may impact education quality. This means that not all courses within a program should require higher-order skills to be assessed; some courses may still need to assess lower-order skills based on Bloom's Taxonomy [26], as they may be important and required by professional bodies. Based on these considerations, the AAA principle categorises assessment practices into three clusters: Against (no generative AI), Avoid (things that generative AI cannot cope well with yet) and Adopt (integrating generative AI into assessments). It is noteworthy that there are two levels of integration within the Adopt cluster, ranging from AI-assisted idea generation and proofreading to partially and fully AI-generated assessment outputs. Figure 1 illustrates the AAA principle through the lens of academic integrity and generative AI integration, while the following sections detail how assessments within each of the three clusters could be presented.

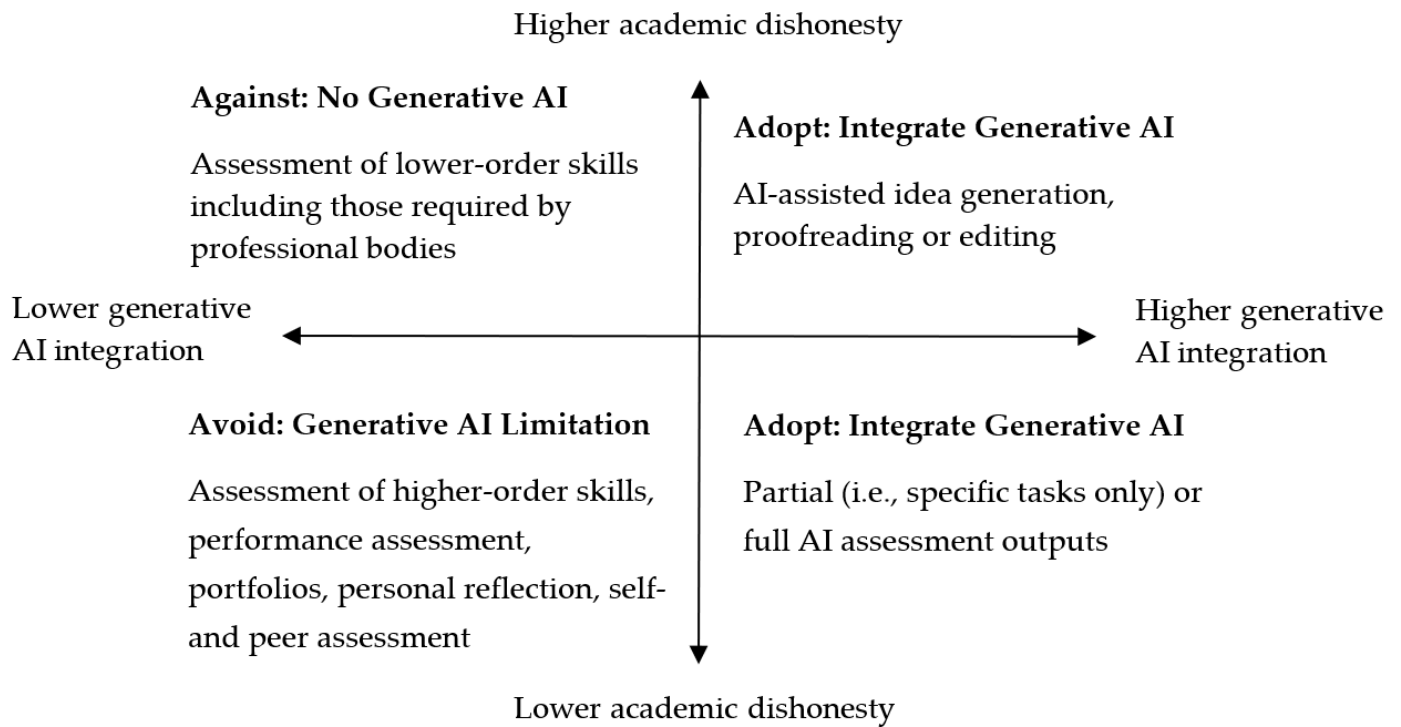


Figure 1. The Against, Avoid and Adopt (AAA) principle: academic integrity vs. AI integration.

4.1. Against: No Generative AI in Assessments

Assessments within this cluster do not permit the use of generative AI in any form. Owing to this, this cluster is appropriate for assessment tasks where it is necessary to assess students' lower-order skills to fulfil requirements set by professional bodies for certification purposes. It is also appropriate for assessment tasks where the use of generative AI is not practical or impossible. Such assessments can be conducted in a generative AI-free examination under invigilation. It can also be used in other forms, such as in class and under supervision, for example, (1) ad hoc question-and-answer sessions that require students to spontaneously interact with their instructors; (2) debate and discussion, which allow for students to be engaged in argumentation, persuasion and reasoning; and (3) viva voce examinations, where students communicate their competencies or mastery verbally to the examiner.

4.2. Avoid: Assessments That Generative AI Does Not Cope Well with (Yet)

In this cluster, assessments are designed so that they are impervious to generative AI. Examples of assessments that generative AI does not cope well with currently include (1) assessments of higher-order skills, as generative AI falls short in tasks requiring complex cognitive abilities such as problem solving, creativity and critical thinking; (2) performance assessment, as generative AI is unable to replace students in demonstrating live presentations or performances in person and real-time; (3) portfolios, as generative AI is unable to present a response that considers the contextual underpinnings of each artefact within a portfolio; and (4) personal reflection, self-assessment and peer assessment, as generative AI is unable to function metacognitively and present the self-reflexivity that students have. Considering these and the fact that generative AI is emerging, the key to designing assessments that are impervious to generative AI is that all these assessments need to be contextualised and relate to personal experience (i.e., by including tasks related to real-world scenarios and personal experiences) and thrive on human interaction.

4.3. *Adopt: Integrating Generative AI in Assessments*

Assessments within this cluster require students to cite the use of generative AI for brainstorming and idea generation, indicate the prompts they used and present the outputs from generative AI.

There are two levels of integration in this cluster. At the lower level, students are permitted to use generative AI for brainstorming and idea generation, but the final submission should not contain AI-generated content (i.e., the final submission must solely be responses from students (or humans)). Generative AI can also be used to proofread and edit the content produced by the students.

A higher level of integration involves the use of generative AI to complete specific parts of their assessment tasks, but the emphasis remains on the human evaluation and validation of the AI-generated content. At this level, students are required to assess and edit AI outputs before the final submission. This approach encourages students to have a deeper understanding of the concepts being assessed. This level of integration can also require generative AI to be fully embedded into the assessment, where the tasks require students to use generative AI, and more importantly, students are required to reflect and improve their responses throughout all their interactions with the generative AI tools.

5. Conclusions

Academic integrity has always been a cornerstone of tertiary educational institutions, given that they traditionally graduate work-ready students to serve society. As the accessibility and proliferation of generative AI become increasingly pervasive, educational institutions will correspondingly need to address the threat of academic dishonesty. This threat is exacerbated if assessment designs and the desired assessment outputs remain largely as they have been since the time of Chinese imperial examinations, which were the first standardised examinations in the world [27].

While presenting considerations and possibilities for redesigning assessments in the face of academic integrity issues related to generative AI, the AAA principle does not require that all assessments be standardised, in-person and invigilated tasks. Based on the purposes of assessments formulated by Archer [18], the AAA principle suggests that assessment tasks that are easily answered by generative AI but are required for certification can continue under proctored conditions (i.e., Against). Tasks that generative AI is less able to cope well with at this moment can include performance assessment, portfolios, personal reflection, self- and peer assessment and assessment of higher-order skills (i.e., Avoid). For preparing students to be future-ready, the AAA principle also presents a cluster of assessments that integrate generative AI (i.e., Adopt), where students are allowed to leverage generative AI for ideation but can only submit purely human-generated content, or where students are required to actively critique, reflect and improve responses generated by AI.

It is envisioned that the AAA principle will remain enduring even with the emergence of multimodal generative AI. Tertiary educational institutions could be guided by it in that they can choose to adopt, avoid or be against generative AI, though fairness and equity issues should be addressed where practical. Nonetheless, it is desirable that educators become acquainted with generative AI tools at a faster rate than students to understand the affordances and limitations of generative AI. This would enable them to identify and clarify acceptable use cases for generative AI within assessments.

Further, generative AI has the potential to enhance teaching by providing personalised learning experiences for individual students. For example, adaptive learning algorithms can already analyse students' performance, preferences and learning styles to tailor content delivery. Instructors can also leverage generative AI to create quality educational content efficiently and use the time saved to focus on facilitative teaching and mentoring. Where facilitative teaching is applied, the instructor's role shifts from being the sole authority to mentoring, guiding and supporting student learning, thereby transforming the learning experience by empowering students, fostering collaboration and emphasising active participation.

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