

Balancing Innovation and Integrity: Addressing the Use of GAI in Student Assessments

Lorna Uden

 <http://orcid.org/0000-0002-8598-7355>

University of Staffordshire, UK

Gregory S. Ching

 <http://orcid.org/0000-0001-9148-0019>

National ChengChi University, Taiwan

Janet Francis

 <http://orcid.org/0000-0002-9843-221X>

University of Staffordshire, UK

ABSTRACT

The advancement of Generative Artificial Intelligence (GAI) tools has led to students increasingly using these tools to generate essays, code programs, and respond to reflective questions, often with minimal or no personal input. This trend challenges traditional notions of authorship, originality, and the learning process. This article examines the implications of GAI use in student assessments. It begins by defining the capabilities of GAI, then explores how students currently utilize these tools and the growing difficulty in detecting such usage. Overcoming the limitations of current detection methods requires a pedagogical shift that incorporates ethical and responsible use of GAI. Additionally, promoting transparency, guiding students on proper attribution, and encouraging responsible GAI usage is essential in fostering academic integrity. Means of progressing these requirements through policy development, curriculum reform, and training for both students and educators are discussed. The article concludes with guidelines for assessment design and areas for future research.

INTRODUCTION

The emergence of Generative Artificial Intelligence (GAI) tools, such as ChatGPT, Claude, and Gemini has introduced significant opportunities and challenges within higher education. GAI refers to

DOI: 10.4018/407452

AI tools based on large language models (LLMs) that can generate coherent and contextually relevant content of various types (including text, programming code, and imagery), that is often indistinguishable from human work (Brown *et al.*, 2020).

While GAI technologies were initially embraced for their potential to support learning and stimulate creativity, they have raised concerns regarding academic integrity, especially in higher education. Recent studies show that a growing number of students rely on GAI to some extent for assignment completion (Cotton *et al.*, 2023; Bulut *et al.*, 2024). This has raised serious concerns about academic integrity, skills development, and authentic student learning.

This chapter begins with a brief review of GAI and its uses in education. This is followed by current methods of detection of GAI content in assessments and their limitations. The next section describes the need to adopt a balanced approach for assessment that requires not only refining detection methods but also rethinking assessment design. A framework is then proposed that integrates GAI as a support mechanism rather than a substitute for learning.

GAI IN EDUCATION

GAI utilises algorithms capable of generating new data by learning from existing data. Unlike discriminative models that classify or predict, GAI models can produce original outputs. Modern GAI systems, utilise transformer-based architectures to model language and image patterns (Brown *et al.*, 2020; OpenAI, 2023). The increasing use of GAI stems from its capacity to automate creative and cognitive tasks previously thought to be the exclusive domain of humans. It can promote productivity gains, enhance personalization, and unlock novel solutions in research and development (Dwivedi *et al.*, 2023). GAI Tools provide platforms, APIs and user interfaces for both developers and non-specialists, thus democratizing access (Bommasani *et al.*, 2021). This section introduces the use of GAI in education and presenting its benefits and the issues around skills acquisition and academic integrity.

GAI for Educators

The use of digital tools for delivery and assessment is not new. An example of the early use of computers in education was the PLATO (Programmed Logic for Automatic Teaching Operations) system (Bitzer, 1976). This provided computer-assisted instruction (CAI) which grew globally throughout the 1970s. CAI systems incorporated reusable recorded and text-based instruction modules followed by tests. They were able to assess textural answers based on the inclusion of keywords and provided alternative feedback dependent on the answer. Computerised adaptive testing (CAT) was developed in the early 1990s and allowed for different questions to be offered based on the ability of the student (Drasgow and Olson-Buchanan, 1999). All students would answer a first question, but the second question offered to each student would be selected based on their first answer. The ability estimate of each student would be continually updated based on their performance. Both CAI and CAT initially utilised item response theory (IRT) rather than machine learning.

With the expansion of the internet in the late 1990s, Learning Management Systems (LMSs) such as Blackboard, Canvas and Moodle began to offer a range of online assessment types such as e-portfolios and quizzes to support different pedagogies as well as collecting data and providing learning analytics. The collection of data led to its use with AI algorithms such as IRT, neural networks and decision trees for im-

22 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:
www.igi-global.com/chapter/balancing-innovation-and-integrity/407452

Related Content

Governing Artificial Intelligence Through Auditing

Alexander Olukaand Pfano Mashau (2026). *Driving Excellence Through AI-Powered Performance Management* (pp. 115-138).

www.irma-international.org/chapter/governing-artificial-intelligence-through-auditing/403942

Behavioral Implicit Communication (BIC): Communicating with Smart Environments

Cristiano Castelfranchi, Giovanni Pezzuloand Luca Tummolini (2010). *International Journal of Ambient Computing and Intelligence* (pp. 1-12).

www.irma-international.org/article/behavioral-implicit-communication-bic/40346

Interaction Per Se: Understanding “The Ambience of Interaction” as Manifested and Situated in Everyday & Ubiquitous IT-Use

Mikael Wiberg (2010). *International Journal of Ambient Computing and Intelligence* (pp. 1-26).

www.irma-international.org/article/interaction-per-understanding-ambience-interaction/43860

Relative Superiority of Key Centrality Measures for Identifying Influencers on Social Media

Yifeng Zhangand Xiaoqing Li (2014). *International Journal of Intelligent Information Technologies* (pp. 1-23).

www.irma-international.org/article/relative-superiority-of-key-centrality-measures-for-identifying-influencers-on-social-media/123941

Indirect Adaptive Fuzzy Control for a Class of Uncertain Nonlinear Systems with Unknown Control Direction

Salim Labiod, Hamid Boubertakhand Thierry Marie Guerra (2013). *Contemporary Theory and Pragmatic Approaches in Fuzzy Computing Utilization* (pp. 139-154).

www.irma-international.org/chapter/indirect-adaptive-fuzzy-control-class/67487