DECODING ACADEMIC INTEGRITY POLICIES: A CORPUS LINGUISTICS INVESTIGATION OF AI AND OTHER TECHNOLOGICAL THREATS

A PREPRINT

Mike Perkins [1*], Jasper Roe [2],

[1] British University Vietnam, Hung Yen, Vietnam.
[2] James Cook University Singapore, Singapore.

[*] Corresponding Author: Mike.p@buv.edu.vn

July 13, 2023

Abstract

This study provides a corpus analysis of academic integrity policies from Higher Education Institutions (HEIs) worldwide, exploring how they address the emerging issues posed by novel technological threats, such as Automated Paraphrasing Tools (APTs) and Generative-Artificial Intelligence (Gen-AI) tools, such as ChatGPT.

The analysis of 142 policies conducted in both November 2022 and May 2023 revealed a significant gap regarding the mention of AI and associated technologies in publicly available academic integrity policies. Despite the growing prevalence of these tools in the six-month period since the release of ChatGPT, no HEIs have produced a revised academic integrity policy. Content analysis of 53 guidance documents produced by HEIs suggests an overall positive perception of Gen-AI tools, with a note of caution.

This study suggests a modification to Bretag' et al.'s (2011) exemplary academic integrity model by introducing "Technological Explicitness", emphasizing the need to include explicit guidelines about new technologies in academic integrity policies. The results underscore the urgent need for HEIs to revise their academic integrity policies, considering the evolving landscape of AI and its implications for academic integrity. This paper argues for a multifaceted approach to deal with the issues of integrating technology, education, policy reform, and assessment restructuring to navigate these challenges while upholding academic integrity.

Keywords Academic Integrity policies, Higher Education Institutions (HEIs), Artificial Intelligence (AI) Tools, ChatGPT, Technological Explicitness, Policy Reform.

Introduction

The state of academic integrity at the close of 2022 presented an optimistic picture, as instances of plagiarism, a form of academic misconduct, decreased between 1990 and 2020 (Curtis, 2022). This positive outlook was further reinforced by the promising role of technology and educational measures in reducing these instances (Curtis & Vardanega, 2016).
However, the increasing use of advanced AI tools, notably Automated Paraphrasing Tools (APTs) and generative-AI (Gen-AI) tools, has introduced new complexities into this landscape. Built on Large Language Models (LLMs) such as GPT3.5 and GPT-4 from OpenAI and integrated into popular software such as ChatGPT, these tools facilitate more subtle forms of plagiarism that challenge detection methodologies (Perkins, 2023; Perkins et al., 2023), sparking a technological 'arms-race' in plagiarism detection (Roe & Perkins, 2022).

This development coincided with a surge of interest in Gen-AI tools, leading to an increase in AI detection tools whose efficacy is questionable, particularly against newer LLMs or when APTs are used to alter the generated text (Perkins et al., 2023). Although there is no definitive proof that the use of APTs or Gen-AI tools by students increased during the COVID-19 pandemic, there is a possibility that academic misconduct did rise during this period (Roe, 2022) In the post-COVID-19 era, the role of digital technology in education has become a significant topic of discussion across various policy levels (Gašević et al., 2022), However, despite the widespread use of digital and AI technologies, only a small percentage of institutions have developed formal policies surrounding their use. This highlights the pressing need for additional research on the institutional policies related to these technologies.
In response to this need, this empirical study offers an in-depth analysis of 142 HEIs' publicly available policies. Our focus was on the frequency of keywords and the presence or absence of terms related to AI, APTs, and Gen-AI tools. Employing corpus linguistics techniques—a systematic textual analysis method that merges quantitative and qualitative approaches (Kennedy, 2014)–we seek to shed light on the stances of HEIs regarding AI technology use. This study not only analyzes the situation during the release of the ChatGPT in November 2022, a moment which has been deemed a 'black swan' event (Nolan & Ghosh, 2023), but also revisits these policies six months later, at the end of May 2023. This two-step approach allowed us to assess how prepared HEIs were for the initial event and how quickly they adapted to the new situation, providing insight into their readiness for future technological developments.
Finally, while Bretag et al. 's (2011) exemplary academic integrity policy model has served as a useful guide for policy formulation, this study proposes enhancements to this model in light of recent technological advancements. In particular, we suggest including a measure of 'technological relevance' to ensure that the model remains responsive to the ongoing evolution of digital tools. The goal is to offer a dynamic and future-proof framework that can effectively uphold academic integrity within the context of a rapidly changing technological landscape.

Literature review

New technological threats to academic integrity

Advancements in technology in recent years have significantly reshaped numerous industries, including academia. The emergence of innovative tools, such as automated paraphrasing tools (APTs) and Generative-Artificial Intelligence (Gen-AI) tools built on large language models (LLMs), has introduced new possibilities for the rapid production of content which may be used to subvert authorship expectations in an assessment scenario. A prime example is ChatGPT, a product of OpenAI's GPT-3.5 and GPT-4 models, which has been the subject of extensive discussion regarding its potential influence on academic integrity (Cotton et al., 2023; Perkins, 2023; Rahman & Watanobe, 2023; Rudolph et al., 2023; Uzun, 2023). These Gen-AI tools can generate remarkably convincing content that is often indistinguishable from human-authored texts, and therefore poses significant challenges for Higher Education Institutions (HEIs), striving to uphold academic standards, and maintaining fair assessments. The sophisticated outputs of these models further complicate the detection of AI-assisted work and raise substantial concerns regarding the authenticity and authorship of academic work (Abd-Elaal et al., 2022; Biderman & Raff, 2022; Fröhling & Zubiaga, 2021; Gunser et al., 2021; Köbis & Mossink, 2021; Liang et al., 2023; Perkins et al., 2023). APTs may be used by students to adjust the output of Gen-AI tools to evade detection by AI text detectors and human assessors alike (Perkins et al., 2023; Sadasivan et al., 2023), or to take text that was originally human written and adjust it so that the original source is obscured (Roe & Perkins, 2022; Rogerson & McCarthy, 2017)

As these tools become more widespread and accessible, they potentially increase the opportunities for misrepresentation and academic malpractice. Some students may use these tools to generate essays, research papers, or other academic assignments without proper attribution, undermining the educational value of these tasks and the credibility of academic institutions (Perkins, 2023; Strzelecki, 2023). Therefore, it is crucial for educational institutions to establish comprehensive guidelines outlining the acceptable use of AI-generated content, and to emphasize the importance of attribution and academic integrity (Crawford et al., 2023; Sullivan et al., 2023).

Students may choose to use APTs or Gen-AI tools to create academic work for many reasons, whether they are aware of the potential implications of academic misconduct or not. One potential cause is the increased accessibility and availability of Internet resources which has been described as leading to a '*cut and paste assembly line'* in the production of academic work (Warn, 2006, p. 195). Furthermore, the growth of the Internet has facilitated access to tools which assist in academic misconduct, such as the advertisement of assignment-writing services for HE students

(Crook & Nixon, 2021). Such cases may represent a starting point for the discovery of other techniques, such as APTs or Gen-AI tools, which are more cost-effective or even free.

Text quality and potential for detection

Existing research has indicated that APTs can produce paraphrased text which retains a high degree of semantic similarity (Wahle et al., 2021), which is difficult to detect, both by humans and software used to detect potential plagiarism (Wahle et al., 2022). Although the usage of current generation APTs has the potential to be identified as such due to the so-called word salad (Rogerson & McCarthy, 2017) that can be produced, the ability of Gen-AI tools to produce significantly improved paraphrases is a significant threat to academic integrity. If LLMs are used to support more advanced paraphrasing which avoids 'word-salad', then existing material accessible to students which posits a strong, clearly identified argument, can be paraphrased in a way that is both undetectable by humans and software tools. Kumar, Mindzak, Eaton, et al. (2022) also highlight how further improvements in LLMs may also lead to an increasing prevalence of contract cheating: as commercial services take advantage of these tools, they can increase the rate at which they are able to produce high-quality outputs that cannot be detected as either being paraphrased from their original source or are entirely generated by LLMs.
The recently available tools provided by OpenAI, such as ChatGPT (OpenAI, 2022)and DALL-E 2 (OpenAi, n.d.), have led to an explosion of interest in how generative AI may affect academic integrity, given the fluency of the created output and its general inability to be detected, even with the aid of AI detection tools (Perkins et al., 2023; Sadasivan et al., 2023). Although emerging evidence has shown that there may be some cases in which techniques may be used to support the detection of AI-generated content (Chakraborty et al., 2023; Christ et al., 2023; Lancaster, 2023), the present evidence strongly suggests that even trained academic staff lack the ability to consistently determine whether text is generated by a current generation LLM or by humans (Perkins et al., 2023).

Past exploration of academic integrity policies

Academic integrity policies play a crucial role in promoting a fair and ethical educational environment in HEIs. Previous studies on HEI academic integrity policies have been conducted in Australia (Bretag et al., 2011; Kaktiņš, 2014; Mahmud & Bretag, 2014), New Zealand (Möller, 2022), Canada (Eaton, 2017; Eaton et al., 2023; Miron et al., 2021; Stoesz et al., 2019; Stoesz & Eaton, 2022), the EU (Foltýnek & Glendinning, 2015; Glendinning, 2013), Latvia and Lithuania (Anohina-Naumeca et al., 2018), and Southeastern Europe (SEEPPAI, 2017).
In Australia, Bretag et al. (2011) explored academic integrity policies across 39 universities, revealing inconsistencies between policies, teaching practices, decision-making, and review processes. Their findings highlight an imbalance between punitive and educative approaches to academic integrity, with many universities lacking clear statements of institutional responsibility for upholding academic integrity standards. Similarly, Kaktiņš (2014) explored the language used in Australian universities' plagiarism policies, revealing that they tended to shift from punitive stances to more educational and pedagogical approaches, viewing students as apprentice researchers. Regarding postgraduate research policies in Australia, Mahmud and Bretag (2014) discovered inconsistencies with the Australian Code for Responsible Conduct of Research and suggested a framework specifically for postgraduate research integrity.

Examining the academic integrity landscape in New Zealand, Möller (2022) assesses the policies of eight public universities against Bretag et al.'s (2011) exemplary standards. The findings underscored that none of the universities met these standards, with several needing enhancement, particularly in terms of access and support. Canada has also emerged as a key location where academic integrity policies have been studied. Eaton (2017) called for a more harmonized approach among Canadian universities to maintain consistency across provinces, while Stoesz and Eaton (2022) criticized the persistently punitive nature of academic integrity policies and the limited support available for students and academic staff in Western Canada. Furthermore, Stoesz et al. (2019) and Miron et al. (2021) identified a lack of specificity for contract cheating in Ontario's academic integrity policies, and suggested opportunities for policy development to promote academic integrity and prevent contract cheating. Eaton et al. (2023) identify inconsistencies across polices and also suggest an update to Bretag et al.'s (2011) exemplary academic integrity model to include an element of 'Equity'.

The EU-wide studies conducted by Foltýnek and Glendinning (2015) and Glendinning et al. (2013) highlighted the variance in academic integrity policies and systems across 27 countries. They utilized an academic integrity maturity model, revealing a stark divide between Western and Eastern EU nations and identifying the UK as having the highest score. These studies have called for concerted efforts to bolster existing policies and practices across the EU.

Latvian and Lithuanian policies, as explored by Anohina-Naumeca et al. (2018), indicate accessibility issues and a lack of systematic institutional approaches to promoting academic integrity. The South-East European studies by Glendinning et al. (2017) and SEEPPAI (2017) highlighted comparable issues, where HEIs mostly fell in the lower to middle areas of academic integrity maturity.

These studies emphasize the significant variability in academic integrity policies across different regions. Themes which have emerged underscore the need for a more educational approach, increased support for students and staff, regular policy reviews and updates, clear definitions and statements of responsibility, and directly addressing emerging threats to academic integrity. The use of Bretag et al.'s (2011) exemplary academic integrity policy model has been instrumental in several studies, providing a robust basis for analysis and policy enhancement. However, no studies have identified policies which satisfy all of the required elements of this model. The ongoing transformations and complexities introduced by technological threats such as APTs and Gen-AI tools require an even more proactive and informed approach to uphold academic integrity in the face of evolving challenges.

While the existing literature provides a comprehensive understanding of academic integrity policies across various countries, a notable research gap remains in terms of a broader understanding of how academic integrity policies are redeveloped in light of new challenges brought about by technological developments. This study fills this gap by exploring the speed at which global HEIs have adapted to emerging threats to academic integrity brought about by Gen-AI tools.

Method

To analyse the academic integrity policies obtained, techniques from corpus linguistics were utilized and supplemented with inductive content analysis. Corpus techniques are used to study large amounts of data and allow researchers to combine both quantitative techniques with in-depth qualitative analysis of large bodies of texts (Freake et al., 2011). A specialized corpus was compiled based on the gathering of publicly available academic integrity policy documents from the HEIs. To gain a balanced view of policies worldwide, a two-pronged strategy was undertaken to achieve a balanced corpus which represents leading institutions in the field of academic integrity. To achieve this aim, we initially focused on the Quacquarelli Symonds (QS) world university rankings, as the most widely read university ranking system. The QS Rankings place 40% of their weight on academic reputation, making the listing highly competitive and representative of the perceived quality of the institution (QS, 2022). First, the academic integrity policies were taken from the online websites of the top ten universities on the Quacquarelli Symonds (QS) rankings from six geographical regions: Africa, Oceania, Europe, North America, Latin America, and Asia. In the event of missing data (as in several regions) or policies unavailable in English, we extended the search to the top 15 institutions in each region. Following this, we expanded the corpus by focusing on university policies of HEIs which are strongly engaged in the field of academic integrity. We achieved this by collecting policies from HEIs that held membership in either the European Network of Academic Integrity (ENAI) or the International Center for Academic Integrity (ICAI). ENAI is a membership-based institution which aims to develop a culture of academic integrity both in Europe and around the world, with 92 member institutions across Europe, Central Asia, India, and North America. The ICAI, founded by the academic integrity specialist Don McCabe in 1992, is credited with developing the six fundamental values of academic integrity on which many HEI policies are built, and has 91 listed member organisations, of which 58 are based in the US, 18 are Canadian, and the remainder come from various countries including Central Asia, Europe, South America, North Africa, and the Middle East (ICAI, n.d.). The inclusion criteria were as follows: First, institutions had to be a HEI, and have a clearly accessible overarching academic integrity policy. By overarching, we mean that the policy was at the university-wide level, rather than belonging to a specific school, discipline, or programme, as initial web searches revealed multiple policies for different schools under the heading of each institution. Furthermore, policies had to be publicly available online, in the English language, and describe specific policies for the definition and violations of academic integrity or committing to academic misconduct. Pilot searches revealed that terminology varied greatly among institutions, so multiple searches were undertaken using a range of single and multi-word terms including 'honor code', 'academic misconduct policy', 'academic integrity policy', 'student code of conduct', 'plagiarism policy', and 'cheating policy'.

The way policies were communicated varied, from a downloadable PDF document to a website which combined policy details with educational multimedia such as videos, quizzes, and links to external organisations such as ICAI.

In these cases, page(s) that best fit our aim of capturing the detailed policies to be communicated to students were selected for inclusion in the corpus.

The initial period of data collection was carried out between 29/11/2022-09/12/2022, with the release of ChatGPT by OpenAI occurring on 30 November 2022. Beginning with the search for the top 10 QS-ranked HEIs in the African region, three of the top 10 HEIs in the QS Rankings did not have a publicly available policy. Extending the search to the top 15 HEIs resulted in the collection of required numbers. In Oceania, Europe, and North America, every HEI in the top 10 QS rankings had a publicly available policy. In Latin America, no publicly available policies were found in English, even when extended to the top 15 institutions. After extending the search to the top 15 institutions, ten policies were found in the Asia region. This resulted in 47 policy documents being collected from the QS rankings. For ENAI member institutions, it was determined that 7 of the 42 members were not HEIs and thus were excluded from the study. Of the remaining 35 institutions, 20 had publicly available academic integrity policy documents. Of the 91 ICAI member institutions, three were not classified as HEIs and one was included in the ENAI search as a member of both networks. Fifteen member institutions did not have accessible policies, resulting in 72 policy documents being collected from the ICAI. A total of 142 academic integrity policy documents were collected (Table 1). These were then collated and compiled into a corpus using SketchEngine with 699,738 words of content.

Source	**Academic Integrity Policies Collected**
QS Rankings Africa	10
QS Rankings Oceania	10
QS Rankings Europe	10
QS Rankings North America	10
QS Rankings Latin America	0
QS Rankings Asia	10
ENAI	20
ICAI	72
Total	**142**

Table 1 Source of academic integrity policies

Throughout the process of collecting the policies for compilation, we undertook familiarisation with the data, an important step in enriching the analysis process and developing greater insight, given that a corpus once compiled is essentially decontextualised (Baker, 2006). The corpus was compiled using Sketch Engine, a fourth-generation corpus analysis tool designed for multidisciplinary use (Sketch Engine, 2016). Sketch Engine allows for case-insensitive searching and automatically marks up text, meaning that manual processing is not required (Sketch Engine, 2016). Subsequently, we performed keyword analysis. Keyword analysis can indicate the aboutness of the texts contained in a corpus by comparing the content to a reference corpus. In this case, the EnTenTen corpus, which contains 36 billion words of English across multiple genres, was used. Keyword analysis was performed using the statistical measures offered in the native Sketch Engine interface. We retained the content words, while grammatical words which indicated style rather than aboutness (Baker, 2004) were discarded. Following the Keyword analysis, we undertook exploratory searches for a range of search terms related to Artificial Intelligence, ChatGPT, LLMs, and APTs to determine their presence or absence in the corpus.
After this initial phase, we returned after a period of six months to compare our findings and identify whether policies had changed in light of the significant impact on academic integrity caused by the release of and subsequent worldwide interest in generative AI tools, namely ChatGPT. Between 30/05/2023 and 31/05/2024, all 142 HEIs for which we had obtained academic integrity policies were reviewed to determine whether any changes had been made to the academic integrity policies. Based on the lack of identified changes in any of the initially collected policy documents, we collected supplementary web pages and documents which had been produced by HEIs, providing guidance to faculty and students on AI, and built a second corpus using these documents to conduct a keyword analysis. Following this, we conducted inductive content analysis of the second corpus to identify themes and categories that occur in these supplementary documents.

Results

November 2022 corpus

After adjusting for prepositions, proper nouns, and other grammatical words, the top ten keywords in the first corpus were as follows:

1. Plagiarism
2. Misconduct
3. Dishonesty
4. Integrity
5. Academic
6. Plagiarize
7. Disciplinary
8. Cheating
9. Turnitin
10. Pre-Requisite

Both ‘plagiarism’ and ‘misconduct’ feature as the most ‘key’ single word terms of the corpus. Looking more broadly at the results, it is possible to draw on the notion of the ‘semantic field’, a metaphor which describes the types of objects which are contained within it; for example, a legal semantic field would contain commonly found legal terms such as ‘prison’, ‘investigation’, and ‘trial’ (Morley & Partington, 2009). The semantic field when looking at the frequency and keyword analysis results suggests a focus on rules, discipline, and unacceptable behaviour (i.e. misconduct, cheating, and plagiarism).

In the results of the keyword analysis, both ‘plagiarism’ and ‘misconduct’ feature as the most ‘key’ single word terms of the corpus. The keyword analysis reveals that the main topics or ‘aboutness’ (Baker, 2004) of the corpus relate to acts of misconduct and dishonesty. The keyword analysis states that plagiarism is the most ‘key’ term, indicating a focus on plagiarism as opposed to other forms of academic misconduct. Interpreting this result gives the impression that textual plagiarism is a problem that requires the most attention. ‘Turnitin’ also appeared as a common keyword, which further strengthens that such policies in aggregate focus on textual plagiarism more than other forms of misconduct, given that Turnitin primarily acts as a text-matching software.
Following this, we conducted search queries within the corpus for AI-related terminology, including GPT-3, which was the most advanced version of ChatGPT’s operating LLM at the time of data collection. The results of this study are presented in Table 2.

Term Searched	Number of policies mentioning the phrase in context
Artificial Intelligence/AI	1 (Bow College)
AI software/tool/programme	0
Large Language Model/s	0
Transformers	0
GPT-3	0
Commercial	11
Machine creation/generation	0
Google Translate	0
Translation	5
Paraphrasing	48

Paraphrasing Tools	1 (Bow College)
Automated/Automatic paraphrasing tool	0
Grammarly	0
Writing assistant	0
Third party	18
Collusion	31
Contract Cheating	29
Ghost + (Author/Authorship/Writing/Writer)	8
Spinner/Spinning	1 (Queensland University)

Table 2 Key terms corpus search

Across all regions and policies (bar 1), the absence of clarity regarding AI and associated tools was clear. Only one of the 142 surveyed institutions mentioned AI and APT usage and provided a policy on how these tools should be used. This policy, on further investigation, was updated in 2021, demonstrating that the institution had recognized the threat and instituted formal policies to consider these issues at a relatively early stage and over a year prior to the release of ChatGPT.

Regarding APTs, the term ‘Paraphrasing’ occurred frequently in the corpus, being mentioned in 48 policies. The mention of paraphrasing in many of these instances describes how paraphrasing should be used to avoid being accused of plagiarism. While several policies described the risks of close paraphrasing and patchwriting, in which only minor amounts of content or words were changed or substituted, only one policy mentioned the prohibition and risk of using paraphrasing tools to automatically modify text, and one policy mentioned the use of article and text spinners (a form of APT). While translation was mentioned by five policies, machine-translated text was not mentioned. However, there are clear and abundant mentions of the prohibited practices. The search terms ‘third parties’, ‘contract cheating’, and ‘collusion’ all featured frequently in the corpus. It could be argued that such sentences by their nature cover LLMs and AI tools, given that they are technically ‘third parties’. On the other hand, student writers may misinterpret this, especially given that even aside from the dilemma of when a software may constitute an actor or person capable of being a ‘third party’, research demonstrates students and faculty are unclear on and disagree on what constitutes plagiarism (Belter & du Pré, 2009; Dawson & Overfield, 2006; Ramzan et al., 2012; Roig, 1997, 1999, 2001).

Follow-up May 2023 corpus

Following a 6-month interval, we returned to each of the HEIs websites to identify whether the academic integrity policies had been updated or renewed in light of the release of ChatGPT, Bard, and other Gen-AI tools. The original intention for this study was then to create a secondary corpus with the updated policies and re-run the analysis, while also looking at granular detail at concordance lines which featured ‘AI’, and ‘ChatGPT’. However, upon returning to the HEI websites, we found that none of the 142 institutions had updated their policies. That said, we noticed during our data collection that many institutions launched specific pages and documents to provide information on Gen-AI tools for both students and faculty. We decided to collect these guidance pages and broaden our search to include all pages that specifically referenced Artificial Intelligence, ChatGPT, and Gen-AI tools in relation to student and teacher use in academic work. This led to the collection of 53 webpages and documents from 53 separate HEIs. 27 of the 53 documents came from institutions in the United States and 11 from institutions in Australia. Other contributions come from institutions in Canada (8), Africa (3), Europe (3), and the Middle East (1). When a corpus was created using this documentation, it was comprised of 29,376 words.

While the texts in this secondary corpus are, by nature, not policy documents, we decided that running a keyword analysis would provide the opportunity to see how AI concerns are framed by official institutional guidance or advice. We conducted keyword analysis, and after adjusting for prepositions, proper nouns, and other grammatical words, the top ten keywords were as follows

1. ChatGPT
2. Generative
3. GPT
4. Plagiarism
5. Turnitin
6. AI-Generated
7. Chatbot
8. Integrity
9. Honesty
10. In-text

The results of the keyword analysis revealed that there is a significant focus on ChatGPT, a specific product of the company OpenAI. A frequency search revealed that ChatGPT is mentioned 337 times within this corpus, while other Gen-AI tools, such as Google's Bard, are not mentioned at all. It seems that the keyword 'plagiarism' identifies that the key concern of such informational pages is to provide information on how such tools can be used for this purpose. This is furthered by the focus on 'integrity', and 'honesty'. This suggests that there may be a closer focus on how Generative AI technologies can be used for misconduct rather than how they can support and improve learning. Further analysis was deemed necessary at a more granular level; therefore, content analysis was chosen. We undertook an inductive manifest thematic content analysis of the 52 documents, taking the content at face value (Kleinheksel et al., 2020) and following the thematic content analysis procedures of 'low hovering' over the data, as described by Anderson (2007). Structurally, we followed the example of Kyngäs (2020), focusing on data reduction, followed by data grouping and concept formation through open coding. We followed the structure outlined by Kyngäs (2020), focusing on data reduction, followed by data grouping, and the formation of concepts through open coding. Five categories were developed to describe the general approach that these guidance pages undertook in informing readers about their approach to Generative AI. The results are presented in Table 3.

Codes	Description
Informational	Aimed at describing what Generative AI is to the reader and how it works in a non-technical manner, as well as the risks and benefits of AI use.
Permissions	Explaining how Gen-AI could be used effectively in class and for learning purposes, and where it cannot be used in order to maintain academic integrity.
Expert Opinion	Frequent references to 'asking your instructor' for course specific recommendations on the suitable use of Gen-AI reflects an evolving understanding of these tools' applicability in differing fields.
Under Revision	Reference to an academic integrity policy that is being drafted, updated, or improved to incorporate AI tools more fully.
Positive Focus	A general tone of positivity and encouragement of the use of experimentation and engagement with AI as a helpful resource.

Table 3 Inductive manifest thematic categories

These five macro-categories of thematic expressions were found to be highly relevant to the AI documents provided by the institutions. Overwhelmingly, the tone and approach taken towards Generative AI was one of optimism and encouragement. The documents referenced the importance of embracing technology in learning and assessment for both the faculty and students. This contrasts directly with the expected results from the keyword analysis. The focus of keywords on academic integrity and honesty suggests that much like the originally collected policies, there may have been a focus on punitive measures, rules, and regulations. However, this was not the case, and the focus tended to be on encouraging the use of AI technologies to aid learning, with a cautionary note to avoid using them for activities that may lead to accusations of plagiarism. Furthermore, many of the documents took an approach to explaining Gen-AI in simple terms and describing its capabilities, carefully addressing the fact that Gen-AI tools such as ChatGPT have limitations and are not capable of producing entirely original work. The tone of the documents seeks to positively engage with AI and explain it to readers while achieving a balanced, cautioned approach against its use for academic misconduct.

Many examples of these texts stated that, despite encouraging AI, caution had to be taken not to violate the rules of academic integrity. In nearly all the identified cases, the risk was of misrepresenting authorship and, thus, using tools such as ChatGPT to engage in textual plagiarism. None of the documents prohibited the use of Gen-AI tools in their entirety, although several identified specific use cases that constituted academic misconduct and listed their associated penalties. Finally, a common theme was a reference to an improving, updated, or in-process policy document which would cover Gen-AI in more detail. This suggests that HEIs believe that a further period of adjustment is necessary to allow them to craft more carefully worded and comprehensive approaches to using Gen-AI in teaching and learning.

Discussion

Policy keyword analysis

The results of the keyword analysis in the original corpus, collected in November 2022, demonstrate that in these public-facing texts, there is a significant focus on the student as the reader and subject of the documents and that such documents tend to be constructed with a focus on rules, procedures, and discipline. The keyword analysis reveals that the main topics or 'aboutness' (Baker, 2004) of the corpus relate to acts of misconduct and dishonesty. Further qualitative analysis of purposively sampled concordances revealed regional differences. North American universities more frequently relied on an 'honour code' rather than a 'misconduct policy', which tended to favour brevity and reference values, rather than specific acts and tools which may or may not constitute academic misconduct. Such occurrences are surprising, as prior research (McCabe et al., 1999) has suggested that honor code values lie in clarifying expectations, which makes it more difficult to rationalize cheating behaviours. If specific policies governing the acceptability of tools are not included in such codes, then gray areas remain.

Across all regions and policies (bar 1), the absence of clarity regarding AI and associated tools was clear. Only one of the 142 institutions surveyed in both November 2022 and May 2023 mentioned AI and APT use as specifically prohibited. Regarding APTs, the term 'paraphrasing' occurred frequently in the first corpus and was mentioned in 48 policies. The mention of paraphrasing in many of these instances describes how paraphrasing should be used to avoid being accused of plagiarism. While several policies described the risks of close paraphrasing and patchwriting, in which only minor amounts of content or words were changed or substituted, only one policy mentioned the prohibition and risk of using paraphrasing tools to automatically modify text, and one policy mentioned the use of article and text spinners (a form of APT). While translation was mentioned by five policies, machine-translated text was not mentioned. However, there are clear and abundant mentions of the prohibited violations. The search terms 'third parties', 'contract cheating', and 'collusion' all featured frequently in the corpus. Third parties were mentioned in 85 policies, contract cheating in 84 policies, and collusion in 89 policies. It could be argued that such sentences by their nature cover LLMs and AI tools, given that they are technically 'third parties'. On the other hand, student writers may misinterpret this, especially given that even aside from the dilemma of when a software may constitute an actor or person capable of being a 'third party', research demonstrates students and faculty are unclear on and disagree on what constitutes plagiarism (Belter & du Pré, 2009; Dawson & Overfield, 2006; Ramzan et al., 2012; Roig, 1997, 1999, 2001). Our familiarization with the policies and the subsequent keyword analysis of the policies collected in November 2022 indicated that there was a focus on a rule-driven, prescriptive approach to the communication of academic integrity policy. Our secondary keyword analysis of the May 2023 Gen-AI advisory documents initially suggested the same pattern. On closer inspection, and then after the thematic content analysis, we found that this was not the case, and that there was a tendency to regard the use of Gen-AI as positive and encouraging, although there were still cautionary notes regarding plagiarism and integrity violations. In summarising the findings, it seems that, despite the six-month period between data collection points, HEIs still adopt a positive, experimental, and uncertain approach to guiding students and staff on the use of Gen-AI tools. This is furthered by the common disclaimer, reminding students to 'ask their teacher' or defer to the course instructor for further guidance. This individualized, faculty-driven approach deflects responsibility and potentially increases student confusion. Furthermore, there is little focus on existing tools such as APTs and their applicability alongside technologies such as ChatGPT, which is an urgent matter, given that they can be used to avoid Gen-AI text detectors (Sadasivan et al., 2023).

Implications for HEIs

HEIs now face the challenge of appropriately integrating Gen-AI tools into academic settings, while maintaining academic integrity. As established by Wilder et al. (2021), the obligation to uphold academic integrity has significantly shifted owing to the increasing prevalence of AI. Consequently, as noted by Dinneen (2021), it is vital that the current 'silence' surrounding the acceptable usage of digital tools in academic institutions is addressed effectively and comprehensively. The accessibility of academic integrity policies and their formalization is a significant concern. Echoing the findings of Anohina-Naumeca et al. (2020), many of these policies were not easily available and several were not structured as conventional policy documents. Given that these policies are primarily intended for students, it is incumbent on HEIs to improve the accessibility of these policies, as suggested by Möller (2022).

The first step is to amend academic integrity policies to explicitly delineate guidelines pertaining to the use of Gen-AI tools and other modern technological threats to academic integrity. To maintain relevance and clarity, academic integrity policies must be updated frequently to provide explicit instructions regarding the acceptable and unacceptable applications of AI tools, as well as any associated penalties that violations of the policy may incur. Such updates can not only reduce potential misinterpretations, but also establish the consequences of policy breaches, thereby improving student compliance. HEIs have a substantial responsibility to ensure that their academic integrity policies are accessible, comprehensible, and relevant to the students who are their primary audience (Möller, 2022). Given the frequent lack of specific guidelines for emerging issues, such as AI and associated tools, this can create ambiguity for students attempting to navigate academic integrity. The fact that no formal policies have been created in the six-month period since the release of ChatGPT demonstrates the delicate balance between the need to maintain academic integrity and embracing new technological advances. This may also suggest a reluctance from HEIs to take a clear stance on the use of Gen-AI tools, which could be compounded if the individuals responsible for creating the policies have limited firsthand experience with the tools being regulated. This could lead to difficulties in formulating nuanced and comprehensive policies that accurately address the evolving challenges posed by these new technologies.

While establishing clear policies is crucial, ensuring the effective implementation of these policies is equally important. To this end, training academic staff to identify the use of AI tools in student work and respond appropriately are essential. This training should extend beyond mere recognition of AI-generated text, and include strategies for handling instances of academic dishonesty involving AI tools. As the development of AI tool detection methods continues to mimic an 'arms race' (Roe & Perkins, 2022), HEIs need to consider how any such detection tools may be utilized in assessment settings, especially given the potential for false positives to occur (Turnitin.com, n.d.) in detection, especially when the text being evaluated is written by Non Native English Speakers (NNES) (Fröhling & Zubiaga, 2021; Liang et al., 2023). In addition to training academic staff, educating students about the appropriate and ethical use of AI tools is an integral part of this holistic approach. As suggested by Perkins et al. (2020), such educational initiatives can effectively reduce instances of plagiarism and other forms of academic misconduct. These initiatives could encompass broader academic integrity training programs and smaller, more specialized group sessions for students who have previously violated integrity policies. Considering the likely future integration of AI tools in professional and academic arenas, teaching students the responsible use of these tools can significantly contribute to their academic and professional success.

The current trend demonstrated in the results regarding the overall acceptance of AI tool usage also prompts a re-evaluation of the traditional modes of assessment. As AI tools become increasingly sophisticated and accessible, the likelihood of their misuse in traditional assessments has increased. To counter this, HEIs might consider the integration of authentic assessments that require students to apply their knowledge in real-world contexts, such as authentic assessment (Darling-Hammond & Snyder, 2000), valid assessment (Brown & Glasner, 1999) and Assessment for Learning (Brown, 2005; Wiliam, 2011). These approaches could facilitate deeper learning, increase critical reflection within assessments, and significantly reduce opportunities for misuse of AI tools. Consideration should also be given to the multiple approaches to how Gen-AI tools could potentially be integrated into assessment strategies, ranging from a complete restriction of its use to a requirement of its use to create the content entirely (Furze, 2023).

From the exploration of the 142 academic integrity policies in this study and the wide variety of approaches to various forms of academic misconduct, it is clear that one approach or recommendation towards an AI academic integrity policy that would suit all HEIs is not feasible. The response of HEIs to the increasing prevalence of AI tools in academic settings must be nuanced and multifaceted. From permissive approaches that promote the transparent and ethical use of AI tools to more restrictive policies prohibiting their use, institutions must strike a balance that aligns with their specific context and priorities. By integrating technology, education, policy reform, and assessment restructuring, HEIs can effectively navigate this challenging landscape while maintaining academic integrity and preparing students for an increasingly digital future.

Update to exemplary academic integrity model
Given the challenges identified in a timely update of academic integrity policies to adapt to new technological threats, we propose a modification to Bretag et al.'s (2011) exemplary academic integrity model to enable future researchers to evaluate academic integrity policies in the new era of deeper integration of digital tools into education. Therefore, we propose a new category which could be named "Technological Explicitness." This term captures the idea that policies need to be clear and specific regarding the role and usage of new technologies in the context of academic integrity. Technological Explicitness, as a new aspect of the model, emphasizes that academic integrity policies should explicitly define and explain the acceptable and unacceptable uses of emerging technologies in academic work. This might encompass clarifications about the use of APTs, Gen-AI tools, tools to support in evading the detection of AI-generated content, and more. The aim of this category is not to discourage the use of new technology but to ensure that students understand when and how such tools can be used ethically and responsibly in their academic work. For example, it may be necessary to spell out what constitutes plagiarism in the context of using these tools and when their use might be considered an act of academic misconduct. In doing so, institutions can make their expectations regarding the use of technology clearer to students, help them navigate the often complex landscape of academic writing in the digital age, and simultaneously reduce confusion and the likelihood of unintentional academic misconduct. As AI and related technologies continue to advance and become more ingrained in academic and everyday life, academic integrity policies must evolve accordingly. This suggests that consideration should be given to the frequency of updates to academic integrity policies. The lack of updates to any of the 142 academic integrity policies in the present study demonstrates that this is clearly an area which could be considered for improvement.

Second, the element of 'Access' in Bretag et al.'s (2011)model can be reconsidered in light of the digital era. In this context, access does not simply mean the availability of printable documents for further storage. Rather, it is about ensuring that policies are accessible across a range of devices that students commonly use, including mobile phones. This shift reflects the increasing digitalization of student life and the necessity for policies to be as readily available as possible. Many of the clearest and user-friendly academic integrity policies and information were not presented as PDFs but were sub-sites involving multimedia content. If we consider students to be key stakeholders in the development of academic integrity policies, information on this subject should be more accessible, highlighting the importance of user-friendly digital platforms for disseminating policies and information related to encouraging academic integrity among students.

Limitations

This study, while providing a comprehensive analysis of the challenges and considerations that HEIs face concerning the use of AI tools, has several limitations that need to be acknowledged. The lack of academic integrity policies from Latin American HEIs in the English language is a considerable limitation which might have skewed the results and restricted our ability to make comprehensive comparisons across different geographical regions. Furthermore, the lack of publicly available policies suggests that some HEIs may have in-house academic integrity policies that we could not analyse, further limiting the comprehensiveness of our analysis. This raises concerns about whether our study fully captures all the measures adopted by HEIs to handle the influence of AI tools on academic integrity.

Adding to the complexity of the issue, the definitions of plagiarism and misrepresentation used in academic integrity policies are often broad, leading to ambiguity. While such broad definitions provide flexibility to HEIs to determine penalties for any identified usage of Gen-AI tools, they can also create confusion among students regarding the acceptable use of these tools. This lack of clarity can potentially lead to various challenges for educators and students. The cultural context further complicates this issue given the context-sensitive nature of plagiarism. As such, the lack of publicly available policies may partly reflect cultural nuances that influence the definitions and perceptions of plagiarism and misrepresentation. This underscores the need to understand and incorporate cultural factors when crafting and implementing policies on academic integrity.

Conclusion

This research presents an examination of how academic integrity policies in HEIs across the world have addressed the emerging issue of the use of students of new technological threats to academic integrity, such as Gen-AI tools. Our analysis of 142 such policies, first conducted in November 2022 and then updated in May 2023, revealed a significant gap in these policies concerning the role and use of AI tools and other emerging technologies in academia. In light of these findings, this study underscores the urgent need for institutions to reassess and revise their academic integrity policies and to address the challenges and considerations of AI in academia.

Our analysis found a striking lack of specificity and clarity in these policies concerning the acceptable and unacceptable uses of AI tools. We propose a modification to Bretag et al.'s (2011) exemplary academic integrity model to better meet the challenges of the digital age. This proposed modification, termed "Technological Explicitness", emphasizes that academic integrity policies should explicitly outline the role of AI tools and other emerging technologies in academia, and clarify the ethical boundaries of using these tools in academic work. The various modes in which HEIs have communicated their current views on Gen-AI tools highlights that accessibility and clear communication are crucial elements of effective academic integrity policies, therefore the model element of 'Access' should also refer not just to the availability of policies, but also to their digital accessibility, comprehensibility, and relevance to the students who are their primary audience. Given that the rapid advancement and increasing sophistication of AI tools pose novel challenges to academic integrity, as AI tools become increasingly ingrained in academic and everyday life, institutions must remain vigilant and proactive in adapting their academic integrity policies to these evolving circumstances. This requires a commitment to regularly update these policies, as well as ongoing training of academic staff to identify and appropriately respond to instances of academic misconduct involving AI tools, as well as educating students about the ethical use of these tools.

Given the cultural and institutional diversity within the global HEI community, no one-size-fits-all solution exists. Rather, institutions must take a nuanced, multifaceted approach to address the challenges posed by AI. By integrating technology, education, policy reform, and assessment restructuring, HEIs can effectively navigate these challenges, uphold academic integrity, and prepare students for an increasingly digitalized future. Despite the limitations of our study, including the lack of easily accessible academic integrity policies and the broad definitions of plagiarism and misrepresentation used in these policies, we believe that our research provides valuable insights and a roadmap for HEIs to manage the policy challenges posed by AI tools.

Declarations

Funding

No funding was received for this study.

Conflict of interest

The authors declare that they have no conflicts of interest.

Gen-AI tool usage disclaimer

The production of this manuscript was supported with the use of the GPT-4 LLM (accessed through ChatGPT) for draft text production. The authors reviewed all output and take full responsibility for the accuracy of the content presented.

References

Abd-Elaal, E.-S., Gamage, S. H., & Mills, J. E. (2022). Assisting academics to identify computer generated writing. *European Journal of Engineering Education*, 1–21. https://doi.org/10.1080/03043797.2022.2046709

Anderson, R. (2007). Thematic content analysis (TCA). *Descriptive Presentation of Qualitative Data*, 1–4.

Anohina-Naumeca, A., Tauginienė, L., & Odineca, T. (2018). Academic integrity policies of Baltic state-financed universities in online public spaces. *International Journal for Educational Integrity*, *14*(1), Article 1. https://doi.org/10.1007/s40979-018-0031-z

Baker, P. (2004). Querying KeywordsQuestions of Difference, Frequency, and Sense in Keywords Analysis. *Journal of English Linguistics - J ENGL LINGUIST*, *32*, 346–359. https://doi.org/10.1177/0075424204269894

Baker, P. (2006). *Using corpora in discourse analysis*. A&C Black.

Belter, R. W., & du Pré, A. (2009). A Strategy to Reduce Plagiarism in an Undergraduate Course. *Teaching of Psychology*, *36*(4), 257–261. https://doi.org/10.1080/00986280903173165

Biderman, S., & Raff, E. (2022). *Fooling MOSS Detection with Pretrained Language Models* (arXiv:2201.07406). arXiv. https://doi.org/10.48550/arXiv.2201.07406

Bretag, T., Mahmud, S., Wallace, M., Walker, R., James, C., Green, M., East, J., McGowan, U., & Patridge, L. (2011). Core elements of exemplary academic integrity policy in Australian higher education. *International Journal for Educational Integrity*, *7*(2), Article 2. https://doi.org/10.21913/IJEI.v7i2.759

Brown, S. (2005). Assessment for learning. *Learning and Teaching in Higher Education*, *1*, 81–89.

Brown, S., & Glasner, A. (1999). *Assessment matters in higher education: Choosing and using diverse approaches*. McGraw-Hill Education (UK).

Chakraborty, S., Bedi, A. S., Zhu, S., An, B., Manocha, D., & Huang, F. (2023). *On the Possibilities of AI-Generated Text Detection* (arXiv:2304.04736). arXiv. https://doi.org/10.48550/arXiv.2304.04736

Christ, M., Gunn, S., & Zamir, O. (2023). *Undetectable Watermarks for Language Models*. https://eprint.iacr.org/2023/763

Cotton, D. R., Cotton, P. A., & Shipway, J. R. (2023). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International*, 1–12. https://doi.org/10.1080/14703297.2023.2190148

Crawford, J., Cowling, M., & Allen, K.-A. (2023). Leadership is needed for ethical ChatGPT: Character, assessment, and learning using artificial intelligence (AI). *Journal of University Teaching & Learning Practice*, *20*(3), 02.

Create and search a text corpus | Sketch Engine. (2016, April 5). https://www.sketchengine.eu/

Crook, C., & Nixon, E. (2021). How internet essay mill websites portray the student experience of higher education. *The Internet and Higher Education*, *48*, 100775. https://doi.org/10.1016/j.iheduc.2020.100775

Curtis, G. J. (2022). Trends in plagiarism and cheating prevalence: 1990-2020 and beyond. In D. Rettinger & T. Bertram Gallant (Eds.), *Cheating academic integrity* (pp. 11–44). Jossey-Bass. https://www.wiley.com/en-au/Cheating+Academic+Integrity%3A+Lessons+from+30+Years+of+Research-p-9781119868170

Curtis, G. J., & Vardanega, L. (2016). Is plagiarism changing over time? A 10-year time-lag study with three points of measurement. *Higher Education Research & Development*, *35*(6), 1167–1179. https://doi.org/10.1080/07294360.2016.1161602

Darling-Hammond, L., & Snyder, J. (2000). Authentic assessment of teaching in context. *Teaching and Teacher Education*, *16*(5–6), 523–545.

Dawson, M. M., & Overfield, J. A. (2006). Plagiarism: Do Students Know What It Is? *Bioscience Education*, *8*(1), 1–15. https://doi.org/10.3108/beej.8.1

Dinneen, C. (2021). Students' use of digital translation and paraphrasing tools in written assignments on Direct Entry English Programs. *English Australia Journal*, *37*(1), 40–51. https://doi.org/10.3316/informit.748262877947586

Eaton, S. E. (2017). Comparative Analysis of Institutional Policy Definitions of Plagiarism: A Pan-Canadian University Study. *Interchange*, *48*(3), 271–281. https://doi.org/10.1007/s10780-017-9300-7

Eaton, S. E., Vogt, L., Seeland, J., & Stoesz, B. M. (2023). *Academic integrity policy analysis of Alberta and Manitoba colleges*. https://hdl.handle.net/1880/116575

Foltýnek, T., & Glendinning, I. (2015). Impact of Policies for Plagiarism in Higher Education Across Europe: Results of the Project. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, *63*(1), 207–216. https://doi.org/10.11118/actaun201563010207

Freake, R., Gentil, G., & Sheyholislami, J. (2011). A bilingual corpus-assisted discourse study of the construction of nationhood and belonging in Quebec. *Discourse & Society*, *22*(1), 21–47.

Fröhling, L., & Zubiaga, A. (2021). Feature-based detection of automated language models: Tackling GPT-2, GPT-3 and Grover. *PeerJ Computer Science*, *7*, e443. https://doi.org/10.7717/peerj-cs.443

Furze, L. (2023). *The AI Assessment Scale: From no AI to full AI – Leon Furze* [Blog]. https://leonfurze.com/2023/04/29/the-ai-assessment-scale-from-no-ai-to-full-ai/

Gašević, D., Tsai, Y.-S., & Drachsler, H. (2022). Learning analytics in higher education – Stakeholders, strategy and scale. *The Internet and Higher Education*, *52*, 100833. https://doi.org/10.1016/j.iheduc.2021.100833

Glendinning, I. (2013). *Comparison of policies for academic integrity in higher education across the European Union*.

Gunser, V. E., Gottschling, S., Brucker, B., Richter, S., & Gerjets, P. (2021). Can Users Distinguish Narrative Texts Written by an Artificial Intelligence Writing Tool from Purely Human Text? *International Conference on Human-Computer Interaction*, 520–527. https://doi.org/10.1007/978-3-030-78635-9_67

ICAI. (n.d.). *Our Member Institutions*. Retrieved June 7, 2023, from https://academicintegrity.org/about/our-member-institutions?force=1

Kaktiņš, L. (2014). Appraising plagiarism policies of Australian universities. *Text & Talk*, *34*(2), 117–141. https://doi.org/10.1515/text-2013-0040

Kennedy, G. (2014). *An introduction to corpus linguistics*. Routledge.

Kleinheksel, A. J., Rockich-Winston, N., Tawfik, H., & Wyatt, T. R. (2020). Demystifying Content Analysis. *American Journal of Pharmaceutical Education*, *84*(1), 7113. https://doi.org/10.5688/ajpe7113

Köbis, N., & Mossink, L. D. (2021). Artificial intelligence versus Maya Angelou: Experimental evidence that people cannot differentiate AI-generated from human-written poetry. *Computers in Human Behavior*, *114*, 106553. https://doi.org/10.1016/j.chb.2020.106553

Kumar, R., Mindzak, M., Eaton, S. E., & Morrison, R. (2022). *AI & AI: Exploring the contemporary intersections of artificial intelligence and academic integrity*. Canadian Society for the Study of Higher Education Annual Conference, Online. Werklund School of Education. https://tinyurl.com/ycknz8fd

Kyngäs, H. (2020). Inductive Content Analysis. In H. Kyngäs, K. Mikkonen, & M. Kääriäinen (Eds.), *The Application of Content Analysis in Nursing Science Research* (pp. 13–21). Springer International Publishing. https://doi.org/10.1007/978-3-030-30199-6_2

Lancaster, T. (2023). Artificial intelligence, text generation tools and ChatGPT – does digital watermarking offer a solution? *International Journal for Educational Integrity*, *19*(1), Article 1. https://doi.org/10.1007/s40979-023-00131-6

Liang, W., Yuksekgonul, M., Mao, Y., Wu, E., & Zou, J. (2023). *GPT detectors are biased against non-native English writers* (arXiv:2304.02819). arXiv. http://arxiv.org/abs/2304.02819

Mahmud, S., & Bretag, T. (2014). Fostering Integrity in Postgraduate Research: An Evidence-Based Policy and Support Framework. *Accountability in Research*, *21*(2), 122–137. https://doi.org/10.1080/08989621.2014.847668

McCabe, D. L., Trevino, L. K., & Butterfield, K. D. (1999). Academic Integrity in Honor Code and Non-Honor Code Environments. *The Journal of Higher Education*, *70*(2), 211–234. https://doi.org/10.1080/00221546.1999.11780762

Miron, J., McKenzie, A., Eaton, S. E., Stoesz, B., Thacker, E., Devereaux, L., Persaud, N., Steeves, M., & Rowbotham, K. (2021). Academic Integrity Policy Analysis of Publicly-Funded Universities in Ontario, Canada: A Focus on Contract Cheating. *Canadian Journal of Educational Administration and Policy*, *197*, Article 197. https://journalhosting.ucalgary.ca/index.php/cjeap/article/view/72082

Möller, A. (2022). An analysis of university academic integrity policies in New Zealand. *Journal of Further and Higher Education*, *0*(0), 1–13. https://doi.org/10.1080/0309877X.2022.2130195

Morley, J., & Partington, A. (2009). A few frequently asked questions about semantic—Or evaluative—Prosody. *International Journal of Corpus Linguistics*, *14*(2), 139–158.

Nolan, B., & Ghosh, S. (2023, May 24). ChatGPT was a black swan event. *Business Insider*. https://www.businessinsider.com/chatgpt-changed-everything-and-was-a-black-swan-event-2023-5

OpenAi. (n.d.). *DALL·E 2*. DALL·E 2. Retrieved November 25, 2022, from https://openai.com/dall-e-2/

OpenAI. (2022, November 30). *ChatGPT: Optimizing Language Models for Dialogue*. OpenAI. https://openai.com/blog/chatgpt/

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). https://doi.org/10.53761/1.20.02.07

Perkins, M., Gezgin, U. B., & Roe, J. (2020). Reducing plagiarism through academic misconduct education. *International Journal for Educational Integrity*, *16*(1), 3. https://doi.org/10.1007/s40979-020-00052-8

Perkins, M., Roe, J., Postma, D., McGaughran, J., & Hickerson, D. (2023). *Game of Tones: Faculty detection of GPT-4 generated content in university assessments* (arXiv:2305.18081). arXiv. https://doi.org/10.48550/arXiv.2305.18081

QS World University Rankings. (n.d.). QS Quacquarelli Symonds. Retrieved December 23, 2022, from https://support.qs.com/hc/en-gb/articles/4405955370898-QS-World-University-Rankings

Rahman, M. M., & Watanobe, Y. (2023). ChatGPT for Education and Research: Opportunities, Threats, and Strategies. *Applied Sciences*, *13*(9), Article 9. https://doi.org/10.3390/app13095783

Ramzan, M., Munir, M. A., Siddique, N., & Asif, M. (2012). Awareness about plagiarism amongst university students in Pakistan. *Higher Education*, *64*(1), 73–84. https://doi.org/10.1007/s10734-011-9481-4

Roe, J. (2022). Reconceptualizing academic dishonesty as a struggle for intersubjective recognition: A new theoretical model. *Humanities and Social Sciences Communications*, *9*(1), Article 1. https://doi.org/10.1057/s41599-022-01182-9

Roe, J., & Perkins, M. (2022). What are Automated Paraphrasing Tools and how do we address them? A review of a growing threat to academic integrity. *International Journal for Educational Integrity*, *18*(1), Article 1. https://doi.org/10.1007/s40979-022-00109-w

Rogerson, A. M., & McCarthy, G. (2017). Using Internet based paraphrasing tools: Original work, patchwriting or facilitated plagiarism? *International Journal for Educational Integrity*, *13*(1), 2. https://doi.org/10.1007/s40979-016-0013-y

Roig, M. (1997). Can undergraduate students determine whether text has been plagiarized? *The Psychological Record*, *47*(1), 113–122. https://doi.org/10.1007/BF03395215

Roig, M. (1999). When College Students' Attempts at Paraphrasing Become Instances of Potential Plagiarism. *Psychological Reports*, *84*(3), 973–982. https://doi.org/10.2466/pr0.1999.84.3.973

Roig, M. (2001). Plagiarism and Paraphrasing Criteria of College and University Professors. *Ethics & Behavior*, *11*(3), 307–323. https://doi.org/10.1207/S15327019EB1103_8

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

Sadasivan, V. S., Kumar, A., Balasubramanian, S., Wang, W., & Feizi, S. (2023). *Can AI-Generated Text be Reliably Detected?* (arXiv:2303.11156). arXiv. https://doi.org/10.48550/arXiv.2303.11156

SEEPPAI. (2017). *South East European Project on Policies for Academic Integrity: Final Report*. http://www.plagiarism.cz/seeppai/Final-report_SEEPPAI.pdf

Sketch Engine. (2016, April 5). *Create and search a text corpus | Sketch Engine*. https://www.sketchengine.eu/

Stoesz, B. M., & Eaton, S. E. (2022). Academic Integrity Policies of Publicly Funded Universities in Western Canada. *Educational Policy*, *36*(6), 1529–1548. https://doi.org/10.1177/0895904820983032

Stoesz, B. M., Eaton, S. E., Miron, J., & Thacker, E. J. (2019). Academic integrity and contract cheating policy analysis of colleges in Ontario, Canada. *International Journal for Educational Integrity*, *15*(1), Article 1. https://doi.org/10.1007/s40979-019-0042-4

Strzelecki, A. (2023). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive Learning Environments*, *0*(0), 1–14. https://doi.org/10.1080/10494820.2023.2209881

Sullivan, M., Kelly, A., & McLaughlan, P. (2023). ChatGPT in higher education: Considerations for academic integrity and student learning. *Journal of Applied Learning and Teaching*, *6*(1).

Turnitin.com. (n.d.). *AI Writing Detection Frequently Asked Questions*. Retrieved May 28, 2023, from https://www.turnitin.com/products/features/ai-writing-detection/faq

Uzun, L. (2023). ChatGPT and Academic Integrity Concerns: Detecting Artificial Intelligence Generated Content. *Language Education and Technology*, *3*(1), Article 1. http://www.langedutech.com/letjournal/index.php/let/article/view/49

Wahle, J. P., Ruas, T., Kirstein, F., & Gipp, B. (2022). How Large Language Models are Transforming Machine-Paraphrased Plagiarism. *ArXiv Preprint ArXiv:2210.03568*. https://arxiv.org/pdf/2210.03568.pdf

Wahle, J. P., Ruas, T., Meuschke, N., & Gipp, B. (2021). Are neural language models good plagiarists? A benchmark for neural paraphrase detection. *2021 ACM/IEEE Joint Conference on Digital Libraries (JCDL)*, 226–229. https://doi.org/10.1109/JCDL52503.2021.00065

Warn, J. (2006). Plagiarism software: No magic bullet! *Higher Education Research & Development*, *25*(2), 195–208. https://doi.org/10.1080/07294360600610438

Wilder, N., Weßels, D., Gröpler, J., Klein, A., & Mundorf, M. (2021). Who is Responsible for Integrity in the Age of Artificial Intelligence? An Analysis Using the Example of Academic Writing. *European Conference on Academic Integrity and Plagiarism 2021*, 179–181. https://tinyurl.com/2s4r5dyr

Wiliam, D. (2011). What is assessment for learning? *Studies in Educational Evaluation*, *37*(1), 3–14.