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Assessment-focused governance mode? Mapping Generative AI policies across 76 UK higher education institutions: Policy framework and recommendations

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Abstract

Higher education institutions are under pressure to develop Generative AI (GenAI) policies in teaching, learning, and assessment. How these policies are framed provides important insights into how the sector is responding to the opportunities and challenges posed by GenAI. This paper examines GenAI policy guidelines published by 76 UK universities, comprising 132 policy and guidance documents. Through qualitative in-depth thematic analysis, we identify five dominant policy themes: institutional positioning on GenAI; assessment design; marking and feedback; teaching and learning; and AI ethics. Our findings reveal an assessment-centred and integrity-first AI governance model. Institutional attention is directed primarily toward safeguarding assessment integrity, preventing academic misconduct and regulating student use of AI in assessed work. By contrast, considerably less attention is given to the pedagogical integration of GenAI into teaching and learning processes. We further find variations across institutions in key policy areas, including AI attribution, AI detection, and AI use in marking and feedback, reflecting broader epistemic, technological and governance uncertainties surrounding the technology in higher education. In response, we propose a policy framework and ten recommendations to support a more balanced approach to GenAI governance. As the first large-scale mapping of GenAI policy across UK higher education, this study makes an original contribution to scholarship on AI governance in education and provides evidence-based guidance for future policy review and development.

Keywords: AI policy framework, AI governance, Assessment, Academic integrity, AI detection, Higher education

Introduction

The rapid development of generative artificial intelligence (GenAI) technologies has created unprecedented challenges and opportunities within higher education. In response to emerging AI technologies, the UK higher education sector has responded differently at different stages. Initially, it was characterised by ad hoc reactions, ranging from outright bans to improvised local guidance, driven by immediate concerns about academic integrity rather than any coherent institutional vision (Atkinson-Toal & Guo, 2024; Cotton et al., 2024). Later, more measured and collective responses emerged, resulting in the involvement of the UK

Department of Education (Department for Education, 2023), alongside a series of sector-wide guidance documents and consultations from bodies such as the Quality Assurance Agency (QAA) (2023a, 2023b) and Jisc (2023). Crucially, in 2023, the 24 Russel Group universities, together with AI experts, developed five guiding principles for AI in education, highlighting the urgency of AI literacy training, sector-wide collaboration and practice sharing (Russel Group, 2023). Despite these early collective efforts, the resulting policy landscape remained fragmented and uneven across institutions (Atkinson-Toal & Guo, 2024; Illingworth, 2026; Wilson, 2025).

While universities raced to implement frameworks, students simultaneously adopted AI technologies at a staggering rate. According to the 2025 Higher Education Policy Institute (HEPI) student GenAI survey across UK universities, undergraduate AI usage surged from 66% to 92% in just one year, while reliance on GenAI in assessment nearly doubled from 53% to 88% (Freeman, 2025). In just one year, the 2026 HEPI student survey (Stephenson and Armstrong, 2026) revealed that AI use is almost universal: 95% of students reported using AI in some manner and 94% of students reported using AI in assessments. In contrast to the widespread student use of AI in education, policy guidance lags behind. Indeed, 41% of UK-degree awarding institutions either have no AI policy or have policies that require institutional login (Illingworth, 2026) and levels of policy development remain highly variable, particularly among non-Russel Group universities (Wilson, 2025).

Although an emerging body of scholarship has begun investigating GenAI policy framework design within universities, the majority of these studies focus on policies in the United States (An et al., 2025; Wang et al., 2024), Hong Kong (Chan and Lee, 2023; Chan, 2023; Chiu, 2024; Chiu, 2024), or broader global scales (Luo, 2024; Jin et al., 2025). The UK higher education context remains understudied, with a couple exceptions focusing on Russel Group universities (Atkinson-Toal & Guo, 2024; Wilson, 2025). A recent sector-wide grey literature report by HEPI (Illingworth, 2026) highlighted the discrepancies of policy language between education & support and detection & surveillance in practice through qualitative coding of 19 policies and quantitative scanning of 96 polices against two pre-designed sets of vocabularies. While these represent vital preliminary diagnoses of an accelerating landscape, they primarily focus

on small samples and refrain from conducting detailed thematic analysis, leaving space for larger scale empirical research.

Our study addresses these limitations. We focus specifically on the UK because its higher education sector, while historically a global leader, is currently navigating a period of financial pressure (Jeffreys & Shearing, 2025; Office for Students, 2025). This renders it uniquely vulnerable to the disruptive structural challenges posed by AI. To comprehensively map the UK higher education AI policy landscape, this paper addresses the following research questions:

1) What are the main themes emerging from AI education policy guidelines?
2) What do these themes indicate about the current state of the AI policy landscape in the UK?
3) What are the broader implications for educational policy and institutional approaches going forward?

To fulfil these aims, we compiled a corpus of GenAI education policies from 76 UK universities, totalling 132 documents and 199,738 words. Our findings reveal that the current policy landscape emphasises assessments and integrity, with a heavy focus on product over process. We find further variations across institutions in key policy areas, with divergences alongside epistemic, technological, and governance uncertainties.

The reminder of this paper is organised as follows. Section 2 surveys the existing literature on higher education AI frameworks, highlighting five dominant themes. Section 3 details our methodology, including policy document collection and the thematic analysis process. Section 4 elaborates on the five themes derived from the thematic analysis. Section 5 critically discusses structural features underpinning the UK's current AI policy landscape, introducing our AI educational framework and a 10-point list of recommendations for drafting educational AI policies. Finally, Section 6 concludes the study by outlining institutional limitations and pathways for future research.

GenAI educational policies in higher education

Following the introduction of generative AI tools into education, many studies have been conducted on the GenAI policies in teaching, learning and assessment (Jin et al., 2025; Xiao et al., 2023; Chiu, 2024; Chiu et al., 2023; Chan, 2023; Saheb and Saheb, 2024; Luo, 2024; Xie et al., 2024; Wu et al., 2024; Temper et al., 2025; An et al., 2025; Humble, 2025; Azevedo et al., 2025; Atkinson-Toal and Guo, 2024). This strand of research has mainly focused on five main themes: 1) developing a GenAI educational policy framework; 2) meta-questions regarding challenges of GenAI policy design; 3) impact of GenAI on assessment and academic integrity; 4) other issues such as equity and supporting students with special learning needs; and 5) the scale of policy region, be it globally or nationally. We survey the five areas of research in details as follows.

Developing GenAI policy framework in higher education

Universities across the world are under pressure to respond to AI and implement effective AI policies. Researchers call for evidence-based approach to policy framework design (Chan and Lee, 2023; Newton, 2025; Chan, 2023; Kofinas et al., 2025). One of the widely cited and early frameworks is proposed by Chan (2023). Based on a survey of 457 students and 180 staff across various disciplines in Hong Kong conducted in 2023, Chan (2023) developed a three-dimensional educational AI framework, encompassing governance, pedagogical, and operational dimensions and detailing the responsible parties of each domain. The governance dimension, managed by senior management, emphasises the governance considerations of AI use; the pedagogical dimension, led by teaching staff, focuses on the teaching and learning aspects of AI integration; and the operational dimension, led by teaching & learning and IT staff, concentrates on the practical implementation of AI in educational settings, including AI literacy training and policy implementation (Chan, 2023). This framework has laid the foundation for ensuing research on framework agenda setting. Jin, et al., (Jin et al., 2025) explored key themes of GenAI integration, analysed communication channels of GenAI policies, and highlighted the roles and responsibilities of faculties, students, and administrators outlined in policy documents. (Wu et al., 2024) expanded the governance structure into information technology, teaching and learning, president and provost,

university libraries, AI centre and additional units by involving more specific university units into the AI governance framework. Taking a step further, Chiu et al. (2023) brought administration to the widely recognised three educational domains — teaching, learning, assessment (Luckin, 2017) — examined the literature in the past ten years regarding AI technologies in education, and summarised 13 roles of AI technologies, learning outcomes, and major challenges in the four key educational domains. Chiu et al., (2023) pointed several challenges facing education, such as lack of AI technologies among teaching staff, lack of integration of AI in teaching and learning process, and digital divide and inequality.

Meta questions on challenges of policy development

The insightful studies on AI framework development also points to another concern in the policy domain, which pertains to the challenges of policy development. AI technologies are advancing rapidly, and the technology application into education domain requires update, so does the corresponding GenAI policies. This is widely recognised by previous literature e.g., (Chiu et al., 2023; Azevedo et al., 2025; Newton, 2025; Wilson, 2025) as well as the AI policies published by consortium of universities (e.g., Russel Group, 2023) and higher education agencies (Department for Education, 2025; Jisc, 2023; UCU, 2026). Jin et al. (2025), identified a range of communication channels for disseminating the GenAI policies, with digital platforms (e.g., university websites, blogs) emerging as the most prevalent channel followed by interactive learning and engagement (e.g., webinars, workshops) and personalised communication methods (e.g., emails, direct contacts). What is more outstanding regarding the policy design, however, is the balance between an effective centralised institutional guidance and academic freedom (Azevedo et al., 2025). While it is important to have an institution-wide central policy on the emerging technology, how AI can be used in different discipline varies and it is essential to preserve space and agency for individual disciplines to devise their own local guidelines (Azevedo et al., 2025; Wu et al., 2024).

Plagiarism, originality and academic integrity in assessment

Embedded and also central to the debates on policy framework and policy design practices is the discussions of plagiarism, academic integrity, and assessment. The common concern is that students' reliance on GenAI tools was an accelerated version of "e-cheating" which lead

to plagiarism, contribute to loss of originality, creativity, and critical thinking, and ultimately leads to erosion of academic integrity (Wang et al., 2024; Kofinas et al., 2025; Gonsalves, 2025; Francis et al., 2026; Francis et al., 2025; Cotton et al., 2024; Chirikov et al., 2026), let alone the impact on students' cognitive abilities (Essel et al., 2024; Zhai et al., 2024). These scholarly reactions were reflected by institutional responses, with Oxford and Cambridge initially banning AI in assessed work while the Russell Group (2023) principles underlined the need for academic rigour and integrity. Similar actions were taken outside the UK. For instance, The Australian state of Queensland have announced they will ban ChatGPT use in state schools, joining New South Wales (ABC News, 2023).

That framing was followed by more nuanced reactions. Other researchers call for re-examination of traditional assessment methods, re-assessment of their fit for purpose (Francis et al., 2025; Francis et al., 2026; Chan and Hu, 2023). Luo (2024) questions the preoccupation with originality as individual property of academic work. The argument went, knowledge production has always been distributed and collaborative (Luo, 2024), particularly when text production is increasing mediated with technologies (Wu et al., 2025). And thus, the current AI challenge requires a redefinition of the concept of originality along a continuous spectrum. Furthermore, the focus on detecting cheating could be distracting from the more fundamental question about the validity of the assessment process. It was noted that AI-detection tools scored below eighty percent accuracy (Weber-Wulff et al., 2023) or can be easily bypassed (Perkins et al., 2024). In addition, Newton (2025) found that UK student self-reports revealed a "profound disconnect" between institutional notions of cheating and the genuinely ambiguous ways in which AI is actually used in academic work.

As a result, calls for a reorientation of assessment practice away from outcome-based surveillance towards process, judgement, and authentic task design began to emerge. These proposals included a focus on developing students' own evaluative judgement as a capacity to assess the quality of both their own work and AI outputs (Bearman & Ajjawi, 2023). Bearman et al., (2024) argue that such a critical approach should encompass three dimensions: evaluating AI outputs, evaluating AI processes, and using AI to assess student judgement itself. It was supported by calls to design assessments that would transform the treatment of generative AI from a threat into a learning tool (Kofinas et al., 2025). These approaches were

formalised in the AI Assessment Scale (AIAS), offering a spectrum of permissible AI involvement calibrated to specific learning outcomes (Perkins et al., 2024). This shift could be characterised by the concept of "postplagiarism" (Eaton, 2023), which asks for a new ethical vocabulary centred on transparency, process, and human-AI collaboration.

Equity, accessibility and digital divide

Another less discussed yet concerning issue in AI policy framework regards equity and digital divide. The focus is on the equitable access to AI tools or technologies (Chan, 2023; Jin et al., 2025; Temper et al., 2025). Students who are from lower income families with less stable internet connectivity may be less able to afford access to AI tools. Moreover, students who are less tech savvy may not understand how the technology works and therefore not able to make good use of the tool. Therefore, universities are tasked with AI literacy training and technology affordances. On the other hand, as Chiu et al., pointed out (Chiu et al., 2023), while previous studies often report increased engagement and skills development, the benefits of AI in education are obtained by the already capable and motivated students. This way, the adoption of AI in education actually widens the existing digital divide. Without education intervention, AI will serve to exacerbate the divide rather than narrow it. On a global level, Xie, et al. (2024) analysed national level AI policies in higher education in China, Japan, Mongolia, and USA, and found that in Japan, AI is mentioned to reduce societal disparities; in China and USA, the equity is focused on eliminating algorithmic discrimination so as to prevent unjust practices. Still, there is a lack of discussion on how to address the digital divide in higher education.

Scale of policy region: US, Hong Kong, EU and globally

Now we move on to a different perspective of examining the literature on AI educational policy. The majority of existing research has focused on polices or policy design in the United States (Wu et al., 2024; Wang et al., 2024; Jiang et al., 2025; Azevedo et al., 2025; An et al., 2025) and Hong Kong (Chan and Lee, 2023; Chan, 2023; Chiu, 2024; Chiu, 2024; Chiu et al., 2023). This might be related to the leading positions in AI technologies and educational research that the two regions currently hold (Chan, 2023). Surprisingly, studies on AI policies in HE in the Europe are only emerging, with (Stracke et al., 2025) investigating 15 policy

documents from universities and governments in 8 EU countries, and (Stracke et al., 2025) (Humble, 2025) analysed policies from 30 Swedish universities. A common theme is the lack of AI policy guidelines and lack of clear effective guidelines. As far as we understand, AI policy mapping in the UK higher education context is scarce with the main focus on Russel Group universities (Atkinson-Toal & Guo, 2024; Wilson, 2025). Wilson (2025) analysed the AI policies in 24 Russel Group universities, and how far these policy guidelines have travelled to AI policies of non-Russel Group universities. His research confirmed the general themes frequently occurring in AI policy guidelines particularly in Russel Group universities, such as assessment and academic integrity, staff and students acceptable use of AI, and overall, AI principles, as well as the lack of AI learning resources in non-Russel Group universities. A handful of studies focus on global AI policies by examining, for instance top 20 world leading universities (Luo, 2024) and a stratified top 10 universities across 6 global regions (Jin et al., 2025). The global perspectives provide a context to understand university policies in individual countries and potentially a benchmark to compare and contrast, though we lack the comprehensiveness on the global scale and the scale of individual country.

To fill this gap, in this study we focus on individual country of the United Kingdom and attempt a comprehensive mapping of its AI policy landscape in higher education institutions. Apart from the "what works" (Bacchi, 2000; Luo, 2024) agenda of policy analysis — identification of key themes, we will also critique the existing policy themes based on what is (overly) represented and what is missing or under-represented. Grounded in the key themes and the critical evaluation of key themes, we devise a GenAI policy drafting framework for higher education policymakers. The framework will chart five domains of GenAI policy themes as well as provide a governance health check for policymakers to stay current in the ever-evolving space of GenAI policymaking.

Data and methodology

In this section, we report the data collection process, including inclusion and exclusion criteria, and the steps of thematic analysis.

Data collection

This study focuses on GenAI in education policy documents published by UK universities. We filtered the universities from the QS World University Ranking 2025[1] to include only UK universities, obtaining 90 universities in the process. From these universities, we gathered institutional-level documentation that features an overarching positioning towards GenAI use or lays out ground rules when, where, and how AI can be used. We only focused on policy guidelines in teaching, learning, and assessment. We excluded those focused on research, marketing or administration, as policies in those areas are specialised for different types of actors (for instance, GenAI policy in administration focuses on admin staff for admin tasks) and have different policy foci (An et al., 2025; Azevedo et al., 2025).

Table 1: Set of selection criteria for GenAI policy documents in education

Inclusion	Exclusion	Explanation
GenAI policy in education, including policy in assessment, teaching, and learning	GenAI policy in research, administration or marketing and other non-teaching and learning focused areas	This research limits its focus on GenAI in education with students learning and staff teaching as focus. Policies in education and in other areas have distinctive focus.
Institution-level guidance	Faculty or department level guidance	The macro-level guidance will be followed by the whole university community regardless of discipline, faculty or department. It stands for high level positioning that a university takes
High-level guidelines/principles, university stance/position statements	Webpages that aim at specific aspect of GenAI use e.g., GenAI literacy, how to write AI prompt	We focused on the overarching principles and guidelines rather than more practical aspects of GenAI literacy, though some policy documents contain fractional AI literacy and instruction statements, the focus is still on high level principles.
Documents in any format, webpage, PDF, or word	Guidelines and policies appearing as news, blogs were excluded	Universities produce documents in different formats for accessibility reasons.

[1] https://www.topuniversities.com/world-university-rankings/2025

To gather relevant policy documents, we searched for terms included "generative artificial intelligence/generative AI/GenAI policies/guidelines/principles", or "university stance/positions on generative artificial intelligence/generative AI/GenAI". We first searched relevant policies on Google by adding the name of university in front of these terms. When this failed to return any useful information, we searched the same term on the universities' homepages to glean any relevant information. We tried to be as inclusive as possible at this stage of data collection, which means all documents about AI and any areas of teaching, learning, and assessment were collected. We then applied the selection criteria, illustrated in Table 1, to sift the most relevant ones for further study.

Eventually, 76 universities were chosen with 132 documents in total, averaging 1.7 documents per university. We did not limit the number of documents from each university, provided they met the selection criteria. Throughout the paper, we used abbreviations (e.g., SOAS) or short forms (e.g., Lancaster) to refer to the university. The lists of the original 90 universities and the link to the final 76 universities can be found in the appendix.

Thematic coding and analysis

We applied thematic analysis to obtain the main themes embedded in the policy documents. The analysis underwent an iterative four-step process, informed by Braun and Clarke (2006) and Chiu (2024b), conducted in ATLAS.ti (version 25.0.1).

Step 1: The first author randomly selected three Russel Group universities and collected their corresponding policy documents. Both authors examined the documents independently, familiarised themselves with the structure and language use. Both authors took notes on the main themes, met and exchanged their initial observations on the major themes they have identified. Previous research indicates that a university's likelihood of having GenAI policies is positively corrected with their academic reputation (Xiao et al., 2023), therefore, by choosing from a pool of Russel Group universities, we are more likely to have the desired policy data to start with. Moreover, Wilson's (2025) study on GenAI policies in 24 Russel Group universities confirm that their AI policies are rather comprehensive, covering many aspects of principles and guidelines regarding AI use in education. The potential comprehensiveness of policy data will facilitate the initial coding of the policy themes. After

discussions, six initial themes were identified: institutional principles and positions on GenAI use; GenAI use in assessment, GenAI use guides for students and staff; GenAI literacy, academic integrity and misconduct, ethics and data privacy.

Step 2: The first author conducted a pilot coding of documents from five Russel Group universities and five non-Russel Group universities to establish the main categories of AI policies. All the universities were randomly selected, using an online random number generator. Both authors read all the collated documents and coded the documents. The categorisation was informed by the initial themes emerging from Step 1 as well as the four key educational domains outlined by Chiu (2024b) — learning, teaching, assessment, and administration. Both authors met again and shared their revised categorisation. A pre-final version of the categorisation emerged from the discussions.

Step 3: The first author coded all the documents that were collated for this study based on the pre-final version of categorisation emerged from Step 2. Some modifications were made, new codes emerged, and some codes were left to decide on which categories to fall into.

Step 4: Both authors discussed to resolve the emerging codes, and refined the themes.

Throughout the paper, we report coding frequencies to provide a general indication of how prevalent each theme (or sub-theme) is across the dataset. We recognise that, although the thematic coding process involved two researchers, some degree of subjectivity is unavoidable in degerming coding boundaries and the number of quotations assigned to a theme. For this reason, rather than reporting the raw number of quotations for each theme, we report the number of universities represented by those quotations and the corresponding percentage. For instance, 79 quotations are coded under the theme “Uphold academic integrity and ensure ethical use of GenAI in education” (Table 2). As these quotations are distributed across 42 universities, we report 42 universities rather than 79 quotations, as the frequency indicator. This approach offers a more robust indication of how widely a theme is distributed across institutions, reduces potential arbitrariness associated with quotation counts, and better aligns with our aim of identifying patterns at the institutional level.

Findings

Five main themes have emerged from these policy guidelines: 1) University positioning on GenAI — high-level institutional principles; 2) GenAI in assessment design — policy aimed at staff designing assessment types; 3) GenAI in assessment marking and feedback — policy regarding grades, feedback, AI assessment scales, and ethical practices; 4) GenAI in teaching and learning — policy on AI use in the actual process of teaching and learning; 5) AI ethics — AI literacy on AI's algorithmic bias, data privacy, social impact and environmental impact of AI. Table 2 gives an overview of each theme.

Table 2: Main themes of GenAI policy in education in UK universities

Main themes	Brief explanation	University mentions(%)
1. Institutional positioning on GenAI	Overarching principles guiding the policymaking of GenAI in education, e.g., support AI literacy training, uphold academic integrity, provide equitable access	64 (84%)
2. GenAI in assessment design	Guidance that staff set regarding use or non-use of GenAI in assessment, including diversifying assessment types and specific guidance on GenAI acknowledgement, references	49 (64%)
3. GenAI in marking and feedback	Specific requirements for using or not using GenAI to assist marking and writing feedback, e.g., whether GenAI detection tools can be used, not uploading students work to GenAI tools, apply human oversight when AI is used; the major theme being acceptable and nonacceptable AI use	64 (84%)
4. GenAI in teaching and learning	Guidance on how to use GenAI to assist the actual teaching practice, e.g., staff preparing slides for teaching, and students using GenAI tools in the classroom	9 (12%)
5. AI ethics	Warning of the algorithmic bias of GenAI, social inequalities associated with unequal access, and its environmental footprint	37 (49%)

As seen from Table 2, the great majority of universities cover the institution-wide GenAI principles (84%), GenAI in marking and feedback (84%), and majority of them cover GenAI in assessment design (64%). However, the policy on GenAI use in the actual pedagogical process

receives the least coverage (12%). Nearly half of universities refer to the potential ethical issues of AI use. We will elaborate on each theme in detail as follows.

Theme 1: University positioning and principles on GenAI in education

Theme 1 regards the overarching principles universities take on GenAI use in education. Most universities highlight their principles at the start of their policy guidelines and reference the Russel Group AI principles. We summarised the seven main principles, as seen in Table 3. The seven principles span across commitment to AI literacy training, supporting staff and integrating AI in curriculum, providing equitable access to GenAI tools, upholding academic integrity, and providing safe space to discuss the use of GenAI in education.

Table 3: Theme 1 Institutional positioning on GenAI

Categories	Sub-categories	University mentions (%)
Principle 1 Support staff and students to be AI literate	Understand how GenAI works Write effective AI prompts Understand bias and social impact of GenAI Understand environmental impact of GenAI tools	43 (57%)
Principle 2 Staff equipped to support student AI use in education	Equip staff with knowledge, tools, and governance structures Equip staff with clear GenAI guidance	27 (36%)
Principle 3 Uphold academic integrity and ensure ethical use of GenAI	Maintain academic integrity, transparency and fairness Ensure responsible, ethical, and critical use of GenAI	42 (55%)
Principle 4 Provide equitable access and reasonable adjustment	Ensure equitable access to AI tools Ensure equitable opportunities to develop AI literacy	15 (20%)
Principle 5 Establish safe space and collaboration to share best practices	Provides safe space to engage in meaningful discussions about GenAI use Hold conversation with staff and students to understand the best practices Engage with employers and external stakeholders to exchange ideas and update employment skills	30 (39%)
Principle 6 Develop students' lifelong skills and employment attributes	Develop students' lifelong employment skills Develop students' AI literacy as graduate attributes	18 (24%)
Principle 7 Co-design and review AIED policy	AIED policy co-creation AIED policy update Reference to existing policy frameworks	34 (45%)

Principle 1: Support staff and students to be AI literate

This is the most frequently mentioned principle regarding AI literacy training for both staff and students. It includes general AI literacy (e.g., what AI is, how to use AI prompts effectively), algorithmic bias of AI, and social and environmental impact of AI tools. It also includes dedicated learning resources, training resources, and governance structure (e.g., GenAI working group in teaching and learning) on GenAI use in education.

Principle 2: Staff equipped to support student AI use in education

AI use in education is fundamentally tied to core education practices, i.e., teaching & learning and assessment, and its effective integration depends heavily on the role of teaching staff. Across institutions, there is a clear recognition that staff are central to operationalising AI within the curriculum. Consequently, most universities demonstrate a strong commitment to providing professional development and training opportunities that enable staff to embed AI in curriculum and teaching. Such support is not merely technical but pedagogical. Teaching staff are expected to redesign learning activities and assessment strategies in ways that incorporate AI while ensuring inclusivity and accessibility for diverse groups of students.

Principle 3 Uphold academic integrity and ensure ethical use of GenAI in education

The second major principle that universities mention regards upholding academic integrity and ensuring ethical use of GenAI. This principle highlights that wherever AI is permitted, it should be used ethically, responsibly, and critically, as seen (1).

(1)

> "*The underlying philosophy and/or ethos surrounding the use of Generative AI at the University of Liverpool is one of promoting literacy around the technology in both students and staff, and using the technology as openly, honestly, and transparently as possible*" (University of Liverpool)

Universities emphasise that the AI ethics protocols are not merely for students to follow, but also for staff members, for instance, disclosing when they use AI to develop contents, highlighting the dual responsibility model (Azevedo et al., 2025).

Principle 4: Provide equitable access and reasonable adjustment

Universities also recognise the digital divide among students — that not all learners may have access to AI tools even where their use is permitted. Some students may be able to afford more advanced models that produce high-quality outputs, while others may rely on free versions or choose not to use AI tools at all for many reasons. Therefore, some universities seek to ensure that all students have access to institutionally approved GenAI tools, enabling them to develop AI skills during their studies. This is summarised in the following quote:

(2)

> "*Not all students will be able to afford or use emergent AI services which could provide some students with an unfair advantage. As such, factors of access must be considered before making AI tools available within in the institution. …. It is proposed that the University should only recommend tools that all students can access or are supported by the University to guarantee equitable access."* (University of Lincoln)

Although Equitable access to AI tools is rather important, it is the least frequently referenced principle. Only 20% of universities acknowledging the need to make GenAI tools available to all students, including those with additional needs.

Principle 5: Develop students' lifelong skills and employment attributes

As some universities argue, AI will be essential for everyday work and hence AI literacy will become an important graduate attribute. It is the universities' responsibility to equip students with the skills and experience of engaging effectively with AI in higher education. The key point is to improve their critical thinking skills and harness AI to as a learning assistant.

Principle 6: Establish safe space and collaboration to share best practices

This guiding principle emphasises the importance of cultivating non-judgemental, safe spaces where diverse stakeholders can routinely discuss the use or non-use of GenAI, while sharing technological perspectives and experiences across diverse contexts. This is particularly important given the rapidly evolving nature of the technology, which dictates that AI use in education remain updated accordingly. Additionally, not all staff and students embrace GenAI,

and some may strongly resist its integration into higher education (e.g., Guest et al., 2025). The priority, as King's College London acknowledges, must be to foster open communication and mutual understanding amid these differing opinions.

(3)

> "*A key aspect to our ongoing and rapidly growing understanding of both the workings of generative AI and the implications of it is that we are all learning, so it is vital that we communicate with one another.*" (King's College London)

As the technology continues to develop, some universities promise to continuously monitor advancements and engage staff and students in discussion about its ethical landscape, and update their AI policies accordingly, which is also part of Principle 7 on regularly updating AI policy.

Principle 7: Co-design and review AIED policy

Alongside actual policy guidelines, universities make meta-level comments on the policymaking process itself. These reflections focus particularly on the co-creation of GenAI policies, the need for regular review and updates, and the practice of drawing on existing policies developed by other institutions. Many universities explicitly state that their GenAI policies are developed through collaborative processes involving the wider university community, typically through consultations with staff and students, dedicated GenAI working groups, or focus groups with relevant stakeholders, as seen in (4)

> "*An artificial intelligence working group has been established to oversee development of policy and resources to support the implementation and use of generative artificial intelligence*." (University of Reading)

In some cases, policymaking extends beyond a single institution and involves cross-institutional collaborations, as illustrated by King's:

(5)

> "*The guidance itself is a result of a cross-institutional collaboration between King's, LSE and the University of Southampton*." (King's College London)

Universities recognise that educational AI policymaking must remain responsive to the rapidly evolving technological landscape. Consequently, they recognise that institutional guidelines should be forward-looking and not seek to implement rules or policies that will be outdated within a short span of time. Policy guidance requires ongoing monitoring and regular updating to ensure continued alignment with emerging developments in AI. This notion is captured in a quote from University of St Andrews:

(6)

> "*Generative AI is a rapidly evolving technology and the University will closely monitor developments, including recommendations from regulators and; practitioners. This Policy will be reviewed biannually to ensure it remains relevant and appropriate.*" (16.1 University of St. Andrews)

Theme 2: GenAI in assessment design

The second theme regards assessment design, which is largely teaching staff's responsibilities. Teaching staff are encouraged to consider a range of key issues related to potential GenAI use before they design an assessment, for instance, whether and how GenAI can be used, specific guidance on how to use AI, and re-thinking the purpose of assignment and considering alternative assignments. These considerations are subsumed under two categories: design principles and design practices, as shown in Table 4.

Table 4: Theme 2 GenAI in assessment design

Category	Sub-categories	University mentions (%)
Design principles	Design assessment that requires authentic and higher-order thinking	23 (30%)
	Diversify assessment types and seek alternative assessment (e.g., in-class quizzes, oral assessments)	
	Emphasise process rather than product	
	Encourage students' reflection on AI use	
Design practices	Provide clear AIED guidance	41 (54%)
	Provide equitable access to GenAI tools	
	Have open conversation with students to co-create and review guidelines	

Universities recognise that assessment can all too often test students' ability to recount theories generated by others (SOAS, n.d.), which is easy for GenAI to replicate. Therefore, they encourage teaching staff to contemplate the purpose of assessment in the era of GenAI (University of Dundee, 2025), for example, the learning outcome and how students can demonstrate these outcomes without easily being replicated by AI. One way is to move to assessment that requires **authentic reflection and higher-order thinking**. As seen in (7), the university recommends authentic assessment that involves students' personal reflection of the learning process and cognitive evaluation. Other universities recommend introducing real-world scenarios that require programme or module-specific knowledge to make it difficult for AI to generalise.

(7)

> "*These qualities can be incorporated into authentic assessments, which are assessments that mirror real-life scenarios, demand cognitive rigor, and necessitate genuine evaluation*." (Canterbury Christ Church University)

Related to emphasis of personal reflection is the shift to higher order thinking skills that require critical analysis, reasoning, evaluation, and creativity, areas where AI is struggling to keep up with human (Essien et al., 2024; Jose et al., 2025; Rondini et al., 2026).

A second principle for assessment design is **emphasising process over product**. This requires teaching staff to assess not just the final outputs (e.g., assignments) but also the learning process that underpins them. Under this principle, students are encouraged to reflect how their learning has developed over time, including how collaboration with peers and the use of assistive technologies has enhanced their learning.

An emphasis on process also underpins the most frequently referenced principle: **diversifying assessment types**. The rapid uptake of AI in student work has prompted universities to re-consider whether traditional assessment types (e.g., essay and exams) remain fit for purpose, or whether there should be a return to invigilated exams. Notably, institutions that address this issue tend to reject a simple reversion to the pen-and-paper format solely to prevent unauthorised AI use. Instead, they emphasise that the primary purpose of assessment is to support student learning and that assessment practices should evolve alongside technological

developments. This reflects calls for assessments to be redesigned to encourage critical thinking

Accordingly, instead of relying on a single assessment format, teaching staff are encouraged to adopt a more varied and integrated approach to evaluating student learning. Alternative assessments suggested in policy documents include in-class quizzes, in-class short-answer tests, oral assessment (class presentations followed by Q&A), follow-up discussions or interviews about submitted work. For instance, in (8), LSE proposes the use of randomised interview, in which a sample of students is selected to discuss their work with examiners as a mean of deterring unauthorised use of GenAI.

(8)

> "*To help safeguard the integrity of essays and other methods of assessment, departments should consider advising students that 10% of all such assessments would be subject to randomised interviews. Students would be advised in advance that some of them would be selected at random to discuss their work with the course leader in order to check against the unauthorised use of GenAI and that the work submitted was the students' own*." (8.4 The London School of Economics and Political Science)

Other approaches include technology-enhanced, observed assessment using platforms like Cadmus, which enable edit-tracking assessment, and video-recording of students' interaction with the assessment tasks., although such technologies introduce their own privacy risks.

In modules/programmes where GenAI use is permitted, students are **encouraged to reflect on the impact of AI use**. This requires critical engagement with AI tools, exploring ways to harness the technology, reflecting on how to best assist their learning, and ultimately, reflecting on what higher education is about. It encourages students to actively develop critical thinking and critical AI literacy as an important employment skills.

Regarding assessment design practices, the most frequent mention is **providing clear, transparent AIED guidance** for students. The guidance covers a range of aspects, including whether GenAI is permitted to use; what is allowed and what is prohibited, rationale of the GenAI use category; templates or guidelines for acknowledgement of AI use, full log of AI

interaction (e.g., the AI prompt used, the screenshot of the conversation with AI), reference and citation style (if required), reminder of GenAI support available, sanctions of misuse of AI. Staff assume the main responsibility of "translating" institution-level policy and guidance to local guidance that students can easily follow (Jiang et al., 2025). Some universities require students to keep record of engagement with AI — for instance, the prompts that are used, screenshots of the AI conversation, and individual learning reflections — and submit the record to substantiate the authorised AI use.

All these require that students have **equitable access to GenAI tools** where their use is authorised. Policy documents indicate that staff bear responsivity for ensuring that all students can access to university-approved GenAI tools. In addition, staff are encouraged to engage in **open conversation with students** to understand how AI is used in practice and to gather feedback on local guidance. However, students may be reluctant to disclose their use of AI due to concerns of academic repercussions or a lack of clarity in guidelines (Gonsalves, 2025), or may instead be more candid with peers than with staff (Attewell, 2025).

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Theme 3: Assessment marking and feedback

The third and the most frequently referenced theme is regarding GenAI use in assessment marking and feedback. This includes whether and how GenAI tools are permitted in student assessments; marking principles and practices for staff; whether GenAI tools are permitted in assessment marking and feedback; and the guidelines of ethical GenAI use.

The majority of universities (61%) have laid out their **GenAI assessment use category system** regarding whether and how GenAI can be responsibly used in assessment. The guidelines fall into two overlapping types: category-based and case-based. In category-based guidelines,

universities usually design a system to regulate the acceptable use of GenAI. The most common category-based guideline is a three-tiered traffic light system: AI use is prohibited (red), AI tools can be used in an assistive way (amber), and AI tools have an integral role and should be used (green), adopted by institutions like Bath, Bristol, Lancaster, LSE and UCL. Other universities adopted a more nuanced category system, usually the AI Assessment Scale (AIAS) developed by Perkins, Furze, Roe and MacVaugh (2024). The AIAS has developed five categories of AI use,: 1) No AI, 2) AI-assisted idea generation and structuring , 3) AI-assisted editing, 4) AI task completion, human evaluation, and 5) Full AI (Perkins et al., 2024). Apart from the category-based guidelines, universities often adopt case-based guidelines where whether AI use is permitted varies per task. For instance, University of Edinburgh recognises that GenAI can be used to "brainstorm ideas, get quick definition of concepts, overcome writer's block through dialogue, check your grammar, organise or summarise information, and re-format your references" (University of Edinburgh, 2025).

Table 5: Theme 3 Assessment marking and feedback

Category	Sub-category	University mentions (%)
Ethical GenAI use, academic misconduct, and consequences	AI attribution: Acknowledgement and referencing Academic misconduct: Passing off AI work as own and no acknowledgement Academic misconduct: Suspicious case handling	36 (47%)
GenAI assessment use category	Case-based guidelines (e.g., brainstorming ideas is acceptable, producing a piece of writing is unacceptable) Category-based guidelines (e.g., RAG traffic light system, Type A, Type B, Type C)	46 (61%)
GenAI in marking and feedback	Allowed Not allowed	12 (16%)
Marking principles	Human oversight and responsibilities Equal treatment with AI and non-AI assisted student work Transparent about staff's use of GenAI in assessment marking	7 (9%)
Marking practices	Not uploading students' assignment to GenAI Request chatlogs and reflective learning logs	12 (17%)
GenAI detection tools	No tools recommended University-approved tools enabled	23 (30%)

Views on staff use of **GenAI in marking and feedback** are notably divided, forming a spectrum from prohibition to conditional and in a small number of cases, comprehensive adoption. At one end of this spectrum, some universities impose a comprehensive ban on its use in the entire assessment processes, including grading and feedback provision. At the other, institutions permit limited use, particularly allowing AI to assist in drafting feedback, as illustrated in the following:

(9)

> "*Where preferred, however, examiners may use these tools to support their own writing in the process of documenting feedback (e.g., consolidating personal notes and rephrasing comments).*" (University of Cambridge)

A smaller number of institutions extend this permissiveness further, allowing AI use across multiple stages of the assessment process. For instances, University of Birmingham allows AI use to support marking, moderation, and feedback generation:

(10)

> "*From the 1 September 2024, and upon the appropriate approval being first received, academic staff can utilise AI systems to support the assessment, grading and moderation of student work along with the provision of individualised student feedback. Where such tools are used, academic staff remain responsible for the academic judgements made on submitted student work and for any feedback they provide for learners*." (University of Birmingham)

Even where AI use is permitted in assessment marking and feedback provision, several common **marking principles** govern its application. First, human judgement and oversight remain paramount. Staff are expected to critically evaluate AI outputs, identify potential hallucinations, and take responsibilities for final decisions, as emphasised in (2). Second, some universities stress the importance of equitable treatment: assessments involving AI should be judged on the same basis as those completed without it. This principle acknowledges an awareness of differing attitudes toward AI use and seeks to accommodate diverse practices. Third, transparency is frequently explicitly required. Institutions expect staff to clearly

communicate to students whether and how AI has been used in the assessment process, as well as the rationale for its use.

Alongside these principles, there are shared **practices** guiding AI use in marking. Most universities prohibit uploading students' work to external GenAI tools, primarily due to concerns over personal data protection and uncertainties surrounding data ownership, as shown in (11).

(11)

> "*Staff should not include any student details or upload work into any GenAI tools without explicit permission. This prevents personal data from being collected, stored, accessed, and shared without consent*." (King's College London)

A smaller subset of institutions adopts a more conditional approach, allowing such practices when institutionally approved tools are used. For example, Bangor University permits the uploading of student work only within university-hosted systems:

(12)

> "*Where this activity needs a student's work to be uploaded to Gen-AI software, staff must only use Bangor University-hosted software for this purpose (e.g. Blackboard, Turnitin, Co-Pilot/Microsoft 365).*" (Bangor University)

Finally, another recurring practice involves requiring students to document their use of AI, including prompts, outputs (e.g., screenshots), and in some cases, reflective accounts of how AI contributed to their work.

In parallel with institutional approaches to AI use in marking and feedback, another focal area within assessment grading and marking concerns the **detection of unauthorised AI use** in student work, typically through embedded tools such as Turnitin's AI writing detection functionality or third-party detectors. Institutional approaches to AI detection vary, but a dominant pattern across universities is a shared scepticism regarding the reliability of the tools.

A majority of universities recognise the limitations of AI detection, particularly their limited effectiveness in accurately identifying AI-generated content. These limitations are frequently framed in terms of the risk of false positives (Paustian & Slinger, 2024), which may in turn leads to false accusations of academic misconduct. In addition, some universities highlight concerns regarding systemic bias in detection technologies, particularly their disproportionate impact on certain student groups, as illustrated in (13).

(13)

> "*In addition to detection tools being inconsistent, the results of such checkers are biased. See for example, this 2023 paper from Stanford researchers: GPT detectors are biased against non-native English writers (https://doi.org/10.1016/j.patter.2023.100779*)" (University of Sussex)

Despite these recognised limitations, a handful of universities permit the use of AI detection tools under specifical conditions. Within these contexts, institutional guidance consistently emphasises that detection outputs should not be treated as definitive evidence. Instead, staff are advised to avoid over-reliance on reported AI scores and to exercise professional judgement when evaluating potential cases of AI misuse, as reflected in (14).

(14)

> "*The University has opted to use this detection tool [Turnitin AI detection], with a watching brief across the sector to understand its effectiveness and limitations. … The University guidance on the use of Turnitin AI detection software advises faculty and professional service staff to not to rely on the detection software and apply professional judgement and knowledge of their students and the context of the assessment when considering whether Gen AI tools have been used*." (Lancaster University)

Theme 4: GenAI in teaching and learning

The theme of GenAI use in teaching (for staff) and learning (for students) receives substantially less attention. References to this area are relatively sparse, with only 12% of universities addressing it explicitly. Where it is mentioned, guidance tends to be fragmented

and illustrative rather than systematic, with no comprehensive frameworks identified across the dataset.

Where institutional guidance does address teaching practices, a recurring pattern is the positioning of GenAI as a supportive tool for early-stage pedagogical design. In particular, universities highlight its use in generating lesson plans, brainstorming ideas, and producing preliminary teaching materials, as illustrated in (15) and (16).

(15)

> "*Generative AI for teaching design-ideas for teaching often come through speaking with colleagues and investigating the pedagogical literature. Generative AI can be used to generate lesson plans, surface new ideas and approaches*." (University of East Anglia)

(16)

> "*If you are developing a new lecture, seminar, workshop, handouts, case studies, simulation scenarios etc. you can also use GenAI tools to help you with initial planning or brainstorming. Tools like Bing Chat or ChatGPT can generate a class outline for you and through further prompting can help you develop this further, expanding the various sections*." (Dundee University)

Despite these examples, the overall level of guidance in this area remains comparatively underdeveloped. Relative to the detailed and procedural guidance observed in assessment-related domains, references to teaching application are typically high-level and indicative.

A similar pattern is evident in relation to students' use of GenAI for learning. Institutional guidance tends to remain general and advisory, rather than prescriptive. The guidelines usually occur in the form of introducing students on effective prompting practices and direct students to consult local course-level policies regarding AI use. Where AI use is allowed, students are typically encouraged to reflect on its potential impact on their learning processes and the development of higher-order thinking skills.

Theme 5: Data privacy, social and environmental impact of GenAI

Table 6: Theme 5 AI ethics

Categories	Sub-categories	University mentions (%)
AI data bias	Algorithmic bias	33 (43%)
	Hallucination, data privacy and copyright	
Social impact	Unequitable access to AI tools	18 (24%)
	Social-economic bias	
	Students with disabilities	
Environmental impact	Carbon emission and water consumption	17 (22%)

This theme concerns the bias and inaccuracy of GenAI generated outputs, and the social impact and environmental impact of Gen-AI tools. First, universities recognise that GenAI models are inherently prone to hallucinations and systemic bias, given that they are trained on non-neutral datasets and operate on statistical probability rather than logical reasoning (Bender et al., 2021). Apart from this, most universities warn against uploading personal or sensitive data to AI platforms as "GenAI companies train their models on content that we submit, this in turn helps them generate income" (University of Dundee, 2025). This warning applies to staff who may use GenAI to assist assessing students' work and students who may use GenAI in their assessment. Related to the algorithmic bias of GenAI, the second sub-theme regards the social bias of GenAI. There are concerns that some platforms have adopted exploitative and unethical ways to train and cleanse their data, for instance, workers in the global south were underpaid to conduct data labelling for some platforms, (1) for instance.

(17)

"*The UK Russell Group of Universities draw attention to an article from Time magazine reporting that the training mechanism for AI tools including exploiting precarious workers in the global south who were paid a very low rate to sift out traumatic and toxic content from the site*." (Birkbeck University of London)

Universities also recognise the inequitable access of GenAI tools. As argued in a MMU policy document, "the pricing of generative AI tools makes access to them inequitable" (Manchester Metropolitan University, n.d.). While most GenAI tools offer their basic models for free, more

advanced versions may perform better. For this reason, some universities offer university approved GenAI platforms so that all students can access the same service without extra payment.

A handful of universities touch upon the topic of GenAI use by students with disabilities. The general sentiment is that students with disabilities are entitled to have reasonable adjustments and more relaxed requirements regarding the use of GenAI. For instance, at Lancaster, the use of the free version of language enhancement applications (LEAs), such as Grammarly, is permitted in assessment and not considered academic misconduct. However, the Premium LEA services are not permitted. For students who have disabilities (locally referred as ILSP), this policy is reasonably adjusted, as seen in (18).

(18)

> "[*D]isabled students with an Inclusive Learning and Support Plan (ILSP) may have been justifiably recommended Grammarly Premium and other similar software to support with grammar and punctuation. Where an ILSP is present this should be considered permission for the student to use software which supports their assessed needs*." (Lancaster University)

Discussion

Our thematic analysis reveals that the current institutional responses to GenAI adopt an assessment-centred and integrity-first mode, dedicating considerably less attention to guiding the actual teaching and learning process. Amid this intense focus on assessment, universities diverge considerably in their core AI practices. These findings indicate that the sector remains reactive rather than proactive, highlighting an urgent need to re-examine where higher education should direct its focus within the broader debate on AI governance.

University policy guidelines prioritise *product* over *process*

Our analysis suggests that universities' policy guidelines heavily privilege the *product* of education (assessed work) over the pedagogical *processes* through which learning and teaching actually occur. This is evident in multiple ways.

First and foremost, there is a disproportionate emphasis on assessment compared to the actual teaching and learning process. As seen previously in Table 3, 64% of the universities cover Theme 2 GenAI in assessment and 84% of them cover Theme 3 GenAI in marking and assessment, compared to only 12% of universities mentioning Theme 4 Teaching and learning.

In other words, the policies offer minimal direction for staff regarding practical integration of AI into teaching preparation and delivery. There is a notable absence of discussion around how educators may responsibly use AI to design learning materials, facilitate interactive learning environments or personalise feedback. This omission reinforces a view of AI as external to the core pedagogical workflow. This may be due to AI policy being largely reactive (Wilson, 2025; Alba et al., 2025), with the default stance being to disallow AI use (Alba *et al.*, 2026). As a result, universities have yet to lead the charge of AI transformation in higher education, and instead largely continue to cling to a vision of education in which written work constitutes knowledge acquisition, with AI technologies a threat to be eliminated from this educational model. However, in other contexts, the integration of AI into pedagogical process is likely to look slightly different. For instance, a study of the top 100 universities in the United States found that slightly over half of the universities (53.8%) encourage and propose the adoption of AI into their teaching workflow, although specific guidelines regarding effective integration are in need.

The contrast between process-focused theme (Theme 4) and product-focused themes (Theme 2 and 3) can be further illustrated in a network diagram showcasing the co-occurrence interaction among the five themes, as seen in Figure 1. The size of Theme 4 Teaching and learning is the smallest among all. It also has the weakest link with the rest of the themes, indicated by only two thin grey lines with Theme 2 and Theme 3. On the other hand, the two assessment themes (Theme 2 and Theme 3) interact with each other and with all the rest of the themes, for instance, both themes have strong connections with Theme 1 Universities'

GenAI policies. This means that whatever appears in the overarching university-wide AI principles are also emphasised in assessment related practices. What is particularly obvious is the missing link between teaching & learning (Theme 4) and the university-wide AI principles (Theme 1), which indicates that integration of AI into the actual teaching and learning process is not considered as one of (main) principles that institutions even consider in the first place. The guidance on AI in teaching and learning seems to be a "lone wolf" that has not been linked to any other AI policy aspects. This is likely because there are insufficient discussions or considerations of integration of AI within everyday teaching and learning practices to coincide with other policy themes.

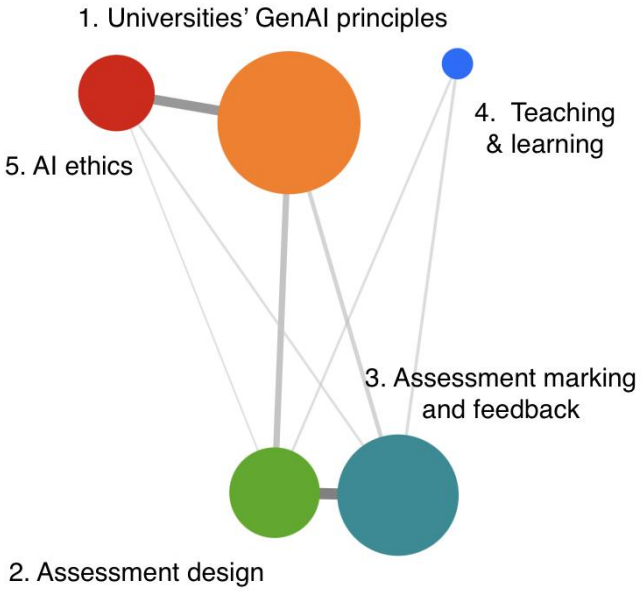


Figure 1: A co-occurrence network of the five themes (a grey line indicates co-occurrence of the themes, or simply one instance is coded under more than one theme; the thicker the line the more frequent the co-occurrence.)

Moreover, the two themes of assessment revolve around students' assignments, detailing the AI assessment scale regarding whether and how AI can be authorised for use in specific modules or assignments, and for teaching staff to produce local, clear guidance on students' use of AI. What is prevalent in the policy guidelines is still deterring academic misconduct by defining a range of AI related practices as plagiarism, such as, unauthorised AI use, using AI without acknowledgement, and passing off AI-generated work as own work. Students' use of

GenAI, if unregulated, is viewed as a threat to originality, and thus a form of academic misconduct. This view may overlook the complexity of the real-world issue of AI use in writing where “knowledge production becomes increasingly distributed, collaborative and mediated by technology” (Luo, 2024, p. 651). To make it even clearly, Wu, et al., (2025) listed a few scenarios of AI use in text production, from entirely AI generated, produced by human with AI-assistance, to AI-revised human-written, and AI providing grammar check. In other words, AI use is on a spectrum. The AI policies are expected to respect the collaborative nature of human-AI in the production process. Currently, it is missing. Therefore, there is a need for clear, transparent policy guidance on what counts as plagiarism and academic misconduct in assessment when GenAI is use, which is also mirrored in recent studies (Chan & Lee, 2023; DeStefano et al., 2026; Newton, 2025).

This is also related to the debate on AI-detectors. While it is notable that the majority of universities acknowledged the limitation of the detection technology and decided not to enable AI detection functionality in their existing software workflow (e.g., Turnitin AI detector), the debate still revolves around “catching” the bad behaviour (i.e., unregulated AI use) exhibited in students’ learning outputs. The focus is still very much on ensuring what is put in the assignment and how the assignment is done still adheres to traditional norms of academic integrity. While this focus is understandable given institutional accountability pressures, it leads to a narrow perception of AI as only a source of academic malpractice (Perkins, 2023). AI is thus framed primarily as a risk to the integrity of students’ final submissions rather than as a tool that may assist learning and teaching processes.

The lack of guidance on meaningful integration of AI in the pedagogical process may indicate that universities are grappling with the technology and have yet to comprehend nor respond to its full potential, which aligns with Wilson’s (2025) findings on AI policy guidance of the 24 Russel Group universities. The lag-behind institutional adoption is in stark contrast with student behaviour — as seen in the 2026 HEPI (Higher Education Policy Institute) Student GenAI survey, 94% of surveyed students reported that they use GenAI to help with assessed work and only 36% report that they feel encouraged by their institution to do so (Stephenson & Armstrong, 2026). Students are generally more optimistic about the adoption of AI in learning (Chan & Lee, 2023; DeStefano et al., 2026). Evidence from other contexts reinforces this point, a recent survey conducted in an R1 university with 166 faculty members revealed

that the majority of staff (63%) seek guidance for meaningful integration of AI into teaching (DeStefano et al., 2026). Universities with existing resources and human power prioritise the quality-check of the student assignments that determines the outcome of students learning. If universities for various reasons cannot lead or guard the pedagogical process, then maintaining the final grace of education quality — deterring plagiarism and academic misconduct — becomes the simplest option.

The rapid development of AI technologies and their integration in education and research have challenged the definition of plagiarism and academic misconduct (Francis et al., 2026; Wilson, 2025). AI has prompted instructors to re-think the foundation of assessment, whether the traditional assessment types are still fit for purpose, and ultimately, the purpose of teaching, learning and the very existence of higher education (Chiu, 2024a; Irving-Walton, 2026). Universities are increasingly governed under neoliberal drive of outputs, metrics, and excellence, all of which build on speed and outputs (Dougherty & Natow, 2020; Sarpong & Adelekan, 2024). Essentially, it leads to performance-based model, in which universities highlight their own comprehensive endeavours while backgrounding the roles of staff and students (Tao et al., 2026). In the area of assessment, the emphasis of outputs of learning in AI policy guidelines reflects this underlying ideology. AI poses challenges like no other, yet it also presents opportunities to harness the technology to advance education in radically beneficial ways.

Divergences in AI use reflected fragmented and reactive policy landscapes due to epistemic, technological and governance uncertainties

The second argument we advance concerns the significance of divergences across institutional GenAI policies. In the analysed policy documents, the great majority of universities (84%) clearly stated their AI principles with the consensus that AI is here to stay in higher education. However, universities diverge in how its use is operationalised in practice. These divergences not only reveal differences in implementation, but reveal deeper epistemic, technical and governance uncertainties surrounding AI in education.

At one level, variation in policies on AI-assisted marking and feedback appears to be shaped by institutional technological affordances. For example, institutions such as The University of

East Anglia (n.d.) and Bangor University (2025) permit AI-supported marking in limited formats (e.g., multiple-choice or short-answer questions) when such functionality is embedded in institution-approved systems. This arguably suggests that the GenAI policy is, in part, infrastructure-led, emerging from what existing systems enable rather than from a coherent pedagogical position on the role of AI in assessment.

More consequential is the divergence in the use of AI detectors. Numerous studies point out that current AI text detection techniques (Wu et al., 2025) have significant limitations, such as the detection techniques plagued by various real world issues and challenges related to LLM-generate texts (Wu et al., 2025); detector are prone to high false discovery rate (Tsigaris & Teixeira da Silva, 2026), available detection tools (either publicly available or commercial tools) are "neither accurate nor reliable" and their performance can be significantly worsened by content obfuscation techniques (Weber-Wulff et al., 2023, p. 1). While the great majority of institutions acknowledge the limitations and risks of current detection technologies and therefore discourage and disallow their use, a minority continue to permit or tacitly enable such tools through integrated platforms (e.g., Turnitin), despite they noted that AI detection score is typically used as a tool rather than the final say regarding potential academic misconduct. Detection or not, this inconsistency points to a lack of sector-wide consensus on evidence-based standards and due process in AI-related academic misconduct. Undeniably and ultimately, consideration of detection serves to deter plagiarism and uphold academic integrity. Whether the ends (academic integrity) will be achieved through the means (detection and outpacing detection) is questionable. Instead, we may want to cultivate a trusting, sustainable culture where individuals champion the ethical, responsible and transparent use of AI tools and other emerging technologies, as researchers have argued (Al-Hashimi, 2026; Tsigaris & Teixeira da Silva, 2026).

Similarly, the near-even split on whether AI outputs should be cited and referenced reflects questions about the epistemic status of generative AI. The argument against citation and reference due to its instability and non-reproducibility of AI outputs is technically valid. However, the absence of shared conventions highlights a broader lack of agreement on how AI-mediated knowledge production should be recognised within academic practice.

These divergences indicate that current AI policies in higher education are fragmented and reactive. While individual flexibility is sometimes necessary, decentralising policy shifts the burden of interpretation and implementation onto local units, such as individual department and module convenors. Furthermore, this approach creates inconsistent expectations for both students and staff across institutions, potentially undermining the coherence in academic standards. More concerning, as Guest, et al., (2025) warn regarding the uncritical adoption of GenAI in higher education, there is the risk of allowing commercial technologies and their affordances to dictate educational policy, rather than policy shaping technology. As corporations like Microsoft integrate chatbots into everyday tools like Word, Outlook, and Teams, it introduces potential for conflicts of interest that threaten the purpose of higher education.

Recommendations for drafting AI educational policy guidelines

Based on the five themes that emerged from the policy data and the two underlying features of the current AIED (AI in education) policy we critically analysed, we developed an AIED policy framework (Figure 2). This framework aims to outline the main policy themes in the current AIED policy landscape and recommend key areas for universities to consider when drafting or updating institutional policies.

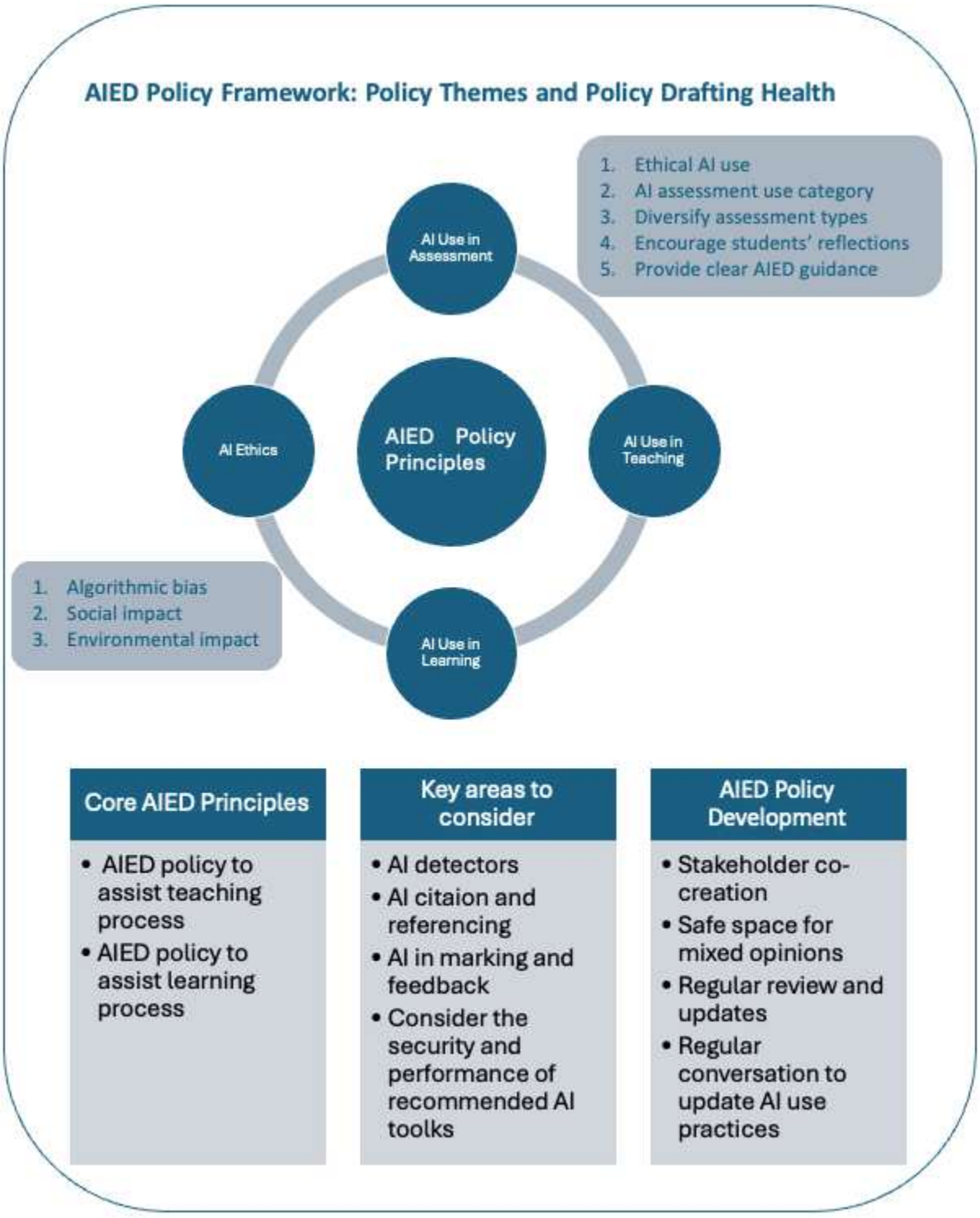


Figure 2 AIED policy framework: Policy themes and policy drafting health check

The framework above summarised the five main themes we have identified in this study. Please note, we highlight AI use in the pedagogical process by splitting the original theme of

GenAI in teaching and learning into two themes and integrating the two assessment themes into one. As our analysis indicates that currently, the guidelines in assessment are relatively comprehensive (e.g., ethical AI practices, AI assessment use categories, diversifying assessment types), and the guidance in the actual pedagogical process is lacking. AI ethics focuses on the algorithmic bias, data privacy, social and environmental impact. The overarching guiding principles integrate with all the other themes.

The three lists at the bottom of the chart summarised our main recommendations for AIED policymakers and policy writers. We would like to remind them of the three areas: whether the AI policy focuses on output or the process; key areas of divergences; considerations of AIED policy creation process. The following 10-point further illustrates the three main areas of recommendations:

1. Consider and develop policy guidance on the use of GenAI to assist the teaching process beyond assessment design, marking, and feedback.
2. Consider and develop policy guidance on the use of GenAI to assist the learning process.
3. Monitor AI detection technology advancement and its risks and take that into account when deciding whether to allow AI detectors in assessment marking and feedback writing.
4. Consider whether citation and reference of AI serve its usual purpose, taking into account the fact that currently GenAI rarely repeats responses to prompts and does not offer a stable source of information.
5. Consider whether and how to allow AI in marking and feedback, considering its method of integration and potential security risks.
6. Consider the security, popularity, and performance of any AI tool recommended or provided by the university.
7. Develop the policy through consultation and co-creation with stakeholders, including, teaching staff, examiners, students, and employers, and clearly delineate the co-creation process in the policy documents.
8. Acknowledge the resistance to AI use in education among students and staff, and create a safe space to allow people who hold different opinions on AI use to share their views and perspectives, as well as practical AI use cases in education.

9. Update and review the policy guidance on a regular basis and clearly indicate the date of review in the policy guidance.
10. Acknowledge the potential inadequacy of policy guidance, and hold regular, open discussions with staff and students about the appropriate and inappropriate uses of AI tools.

These recommendations should be read as serving macro, university-wide guidance rather than meso-level guidance for schools or departments, or micro-level guidance for individual programmes or modules. Nonetheless, certain foundational principles may be globally applied, such as acknowledging diverse perspectives on educational AI use. Given that AI technologies are poised to advance rapidly, pedagogical applications will inevitably evolve, requiring educational policies to keep pace. Consequently, institutional AI policies must be treated as dynamic, iterative framework (Ghimire & Edwards, 2024). For this reason, we deliberately avoid dichotomising practices into rigid categories of "good" or "to be avoided". Instead, we delineate the potential risks of specific approaches, inviting individual universities to make contextualised, informed decisions aligned with the current technological climate. Accordingly, we refrain from endorsing certain practices solely on the basis of widespread institutional adoption, such as disabling AI detection. Furthermore, we would like to emphasise *how* the policy is developed is as just as important as *what* the policy is all about. Therefore, it is crucial to reassure readers about the drafting process, specifically, how the policy was formulated, which stakeholders were consulted, and whether the guidelines are grounded in frontline pedagogical experience or empirical research insights.

Conclusions

We conducted a thematic analysis of Generative AI policy documents in teaching, learning, and assessment across 76 UK universities, identifying five main themes: (1) overall GenAI position and principles, (2) GenAI in assessment design, (3) GenAI in assessment marking and feedback, (4) GenAI in teaching and learning, (5) GenAI ethics. Guidelines on assessment dominate the policy documents, pointing to AI assessment use categories, ethics, and deterrence of plagiarism and academic misconduct in general. In contrast, guidance on the integration of GenAI in the pedagogical practices and processes is significantly lacking. These differences arguably indicate that the current AI policy in education across the UK universities

still emphasise product over process and ultimately point to the underlying cautious and reactive rather than proactive attitudes towards application of GenAI technologies in the higher education sector. There are varying levels of divergences in key AI policy areas, exhibiting epistemic, technological and governance uncertainties in the current educational AI policy landscape.

Based on these findings, we have proposed a five-dimension GenAI policy framework for teaching, learning and assessment in higher education. It encompasses overarching guiding principles, guidelines in teaching, learning, assessment, respectively, and AI literacy on the algorithmic bias, environmental and social impact of GenAI. Furthermore, the framework offers a governance health check for policymakers, including a general principle of recognising the tension between process (teaching & learning) and product (assessment), and areas of policy where they should be mindful of (e.g., AI detection), and considerations of developing AI policy in general (e.g., co-creation, review and regular update).

This study has its own limitations. We only focused on GenAI policy and guidelines in teaching & learning and assessment and excluded those in research, operational use, and other areas (for instance, Manchester has a GenAI policy on marketing and student recruitment). Second, we only focus on the documents and webpages that are publicly available and do not require institutional login. We are aware that some more detailed guidance and policy documents may only be accessed by internal stakeholders such as staff and students, as seen in previous studies, such as Wilson (2025). Third, we only focus on macro-institutional level policy and guidelines and exclude those meso- or micro-level guidance that defines local usage of GenAI. These local guidelines are usually at faculty, department, programme and module level and may not be shared publicly.

Despite the limitations, the findings of our study have significant implications for the scholarship in educational technologies higher education in the UK context. It offers a comprehensive picture of the AI policy landscape in the UK higher education sector by examining a large sample. Moreover, it highlights the issues of the existing policy guidelines and reveals the underlying ideologies of policymaking. For practitioners in the sector, the AIED framework will be a useful reference for developing or updating their own AI policy. The AI

governance health check intentionally refrain from making claims on “good” or “bad” practices, but instead, function as a reminder to contemplate areas of divergences.

Declarations

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The datasets generated and/or analysed during the current study will be made publicly available once it is published.

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The authors declare no competing interests.

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Authors' contributions:

YT: Conceptualisation, Methodology, Formal analysis, Investigation-data collection, Data curation, Writing-original draft, Writing-review & editing, visualisation
MR: Conceptualisation, Methodology, Investigation-data collection, Writing-original draft, Writing-review & editing
FB: Conceptualisation, Writing-original draft, Writing-review & editing
XZ: Conceptualisation, Writing-original draft, Writing-review & editing

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References

Al-Hashimi, B. M. (2026, May 8). Detection tools won't save the scholarly record from the AI paper avalanche. *Wonkhe*. https://wonkhe.com/blogs/detection-tools-wont-save-the-scholarly-record-from-the-ai-paper-avalanche/

An, Y., Yu, J. H., & James, S. (2025). Investigating the higher education institutions' guidelines and policies regarding the use of generative AI in teaching, learning, research, and administration. *International Journal of Educational Technology in Higher Education*, *22*(1), 10. https://doi.org/10.1186/s41239-025-00507-3

Atkinson-Toal, A., & Guo, C. (2024). Generative Artificial Intelligence (AI) Education Policies of UK Universities. *Enhancing Teaching and Learning in Higher Education*, *2*, 70–94. https://doi.org/10.62512/etlhe.20

Attewell, S. (2025, September 2). Staff perceptions of AI 2025. *Artificial Intelligence*. https://nationalcentreforai.jiscinvolve.org/wp/2025/09/02/staff-perceptions-of-ai-2025/

Azevedo, L., Robles, P., Best, E., & Mallinson, D. J. (2025). Institutional Policies on Artificial Intelligence in Higher Education: Frameworks and Best Practices for Faculty. *New Directions for Adult and Continuing Education*, *2025*(188), 70–78. https://doi.org/10.1002/ace.70013

Bacchi, C. (2000). Policy as Discourse: What does it mean? Where does it get us? *Discourse: Studies in the Cultural Politics of Education*, *21*(1), 45–57. https://doi.org/10.1080/01596300050005493

Bangor University. (2025). *Generative Artificial Intelligence Software and Academic Integrity Guidance Document*. https://doi.org/https://www.bangor.ac.uk/regulations/documents/artificial-intelligence-software-assessment-en.docx

Bearman, M., & Ajjawi, R. (2023). Learning to work with the black box: Pedagogy for a world with artificial intelligence. *British Journal of Educational Technology*, *54*(5), 1160–1173. https://doi.org/10.1111/bjet.13337

Bearman, M., Tai, J., Dawson, P., Boud, D., & Ajjawi, R. (2024). Developing evaluative judgement for a time of generative artificial intelligence. *Assessment & Evaluation in Higher Education*, *49*(6), 893–905. https://doi.org/10.1080/02602938.2024.2335321

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? 🦜. *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, FAccT '21*, 610–623. https://doi.org/10.1145/3442188.3445922

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

Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Education*, *20*(1), 38. https://doi.org/10.1186/s41239-023-00408-3

Chan, C. K. Y., & Lee, K. K. W. (2023). The AI generation gap: Are Gen Z students more interested in adopting generative AI such as ChatGPT in teaching and learning than their Gen X and millennial generation teachers? *Smart Learning Environments*, *10*(1), 60. https://doi.org/10.1186/s40561-023-00269-3

Chiu, T. K. F. (2024a). Future research recommendations for transforming higher education with generative AI. *Computers and Education: Artificial Intelligence*, *6*, 100197. https://doi.org/10.1016/j.caeai.2023.100197

Chiu, T. K. F. (2024b). The impact of Generative AI (GenAI) on practices, policies and research direction in education: A case of ChatGPT and Midjourney. *Interactive Learning Environments*, *32*(10), 6187–6203. https://doi.org/10.1080/10494820.2023.2253861

Chiu, T. K. F., Xia, Q., Zhou, X., Chai, C. S., & Cheng, M. (2023). Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. *Computers and Education: Artificial Intelligence*, *4*, 100118. https://doi.org/10.1016/j.caeai.2022.100118

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

Department for Education. (2025). *Generative artificial intelligence (AI) in education*. Department for Education. https://www.gov.uk/government/publications/generative-artificial-intelligence-in-education/generative-artificial-intelligence-ai-in-education

DeStefano, C., Hackney, J., & Moskal, P. (2026). Understanding the Generative AI Divide: Faculty and Student Perspectives in Higher Education. *Online Learning*, *30*(2), 31–48. (US). https://doi.org/10.24059/olj.v30i2.5911

Dougherty, K. J., & Natow, R. S. (2020). Performance-based funding for higher education: How well does neoliberal theory capture neoliberal practice? *Higher Education*, *80*(3), 457–478. https://doi.org/10.1007/s10734-019-00491-4

Eaton, S. E. (2023). Postplagiarism: Transdisciplinary ethics and integrity in the age of artificial intelligence and neurotechnology. *International Journal for Educational Integrity*, *19*(1), 23. https://doi.org/10.1007/s40979-023-00144-1

Essien, A., Bukoye, O. T., O'Dea, X., & Kremantzis, M. (2024). The influence of AI text generators on critical thinking skills in UK business schools. *Studies in Higher Education*, *49*(5), 865–882. https://doi.org/10.1080/03075079.2024.2316881

Francis, N., Smith, D., Kempbell-Karn, K., & Rutherford, S. (2026, April 2). Generative AI exposes longstanding flaws in the use of essay assessments in a mass system. *Wonkhe*. https://wonkhe.com/blogs/generative-ai-exposes-longstanding-flaws-in-the-use-of-essay-assessments-in-a-mass-system/

Ghimire, A., & Edwards, J. (2024). *From Guidelines to Governance: A Study of AI Policies in Education* (arXiv:2403.15601). arXiv. https://doi.org/10.48550/arXiv.2403.15601

Gonsalves, C. (2025). Addressing student non-compliance in AI use declarations: Implications for academic integrity and assessment in higher education. *Assessment & Evaluation in Higher Education*, *50*(4), 592–606. https://doi.org/10.1080/02602938.2024.2415654

Guest, O., Suarez, M., Müller, B., van Meerkerk, E., Oude Groote Beverborg, A., de Haan, R., Reyes Elizondo, A., Blokpoel, M., Scharfenberg, N., Kleinherenbrink, A., Camerino, I., Woensdregt, M., Monett, D., Brown, J., Avraamidou, L., Alenda-Demoutiez, J., Hermans, F., & van Rooij, I. (2025). *Against the Uncritical Adoption of 'AI' Technologies in Academia*. Zenodo. https://doi.org/10.5281/zenodo.17065099

Illingworth, S. (2026). *What UK university AI policies actually do: A study of 96 universities*. HEPI. https://www.hepi.ac.uk/wp-content/uploads/2026/05/What-UK-university-AI-policies-actually-do-A-study-of-96-institutions.pdf

Irving-Walton, J. (2026, April 16). The tensions of AI shouldn't come as a surprise in a system wired for speed and output. *Wonkhe*. https://wonkhe.com/blogs/the-tensions-of-ai-shouldnt-come-as-a-surprise-in-a-system-wired-for-speed-and-output/

Jeffreys, B., & Shearing, H. (2025, May 8). *Four in 10 universities face financial challenges*. BBC News. https://www.bbc.co.uk/news/articles/c8dgdlrdnrgo

Jiang, Y., Xie, L., & Cao, X. (2025). Exploring the Effectiveness of Institutional Policies and Regulations for Generative AI Usage in Higher Education. *Higher Education Quarterly*, *79*(4), e70054. https://doi.org/10.1111/hequ.70054

Jin, Y., Yan, L., Echeverria, V., Gašević, D., & Martinez-Maldonado, R. (2025). Generative AI in higher education: A global perspective of institutional adoption policies and guidelines. *Computers and Education: Artificial Intelligence*, *8*, 100348. https://doi.org/10.1016/j.caeai.2024.100348

Jisc. (2023). *AI in tertiary education: A summary of the current state of play – Third edition*.

Jose, B., Cherian, J., Verghis, A. M., Varghise, S. M., S, M., & Joseph, S. (2025). The cognitive paradox of AI in education: Between enhancement and erosion. *Frontiers in Psychology*, *16*, 1550621. https://doi.org/10.3389/fpsyg.2025.1550621

Kofinas, A. K., Tsay, C. H.-H., & Pike, D. (2025). The impact of generative AI on academic integrity of authentic assessments within a higher education context. *British Journal of Educational Technology*, *56*(6), 2522–2549. https://doi.org/10.1111/bjet.13585

Luo, J. (2024). A critical review of GenAI policies in higher education assessment: A call to reconsider the "originality" of students' work. *Assessment & Evaluation in Higher Education*, *49*(5), 651–664. https://doi.org/10.1080/02602938.2024.2309963

Manchester Metropolitan University. (n.d.). *Embracing generative AI responsibly*. Manchester Metropolitan University. Retrieved 11 June 2026, from https://www.mmu.ac.uk/about-us/professional-services/uta/teaching/embracing-generative-ai-responsibly

Newton, P. M. (2025). How vulnerable are UK universities to cheating with new GenAI tools? A pragmatic risk assessment. *Assessment & Evaluation in Higher Education*, *50*(8), 1332–1343. https://doi.org/10.1080/02602938.2025.2511794

Office for Students. (2025). *Financial sustainability of higher education providers in England 2025*.

Paustian, T., & Slinger, B. (2024). Students are using large language models and AI detectors can often detect their use. *Frontiers in Education*, *9*. https://doi.org/10.3389/feduc.2024.1374889

Perkins, M. (2023). Academic Integrity considerations of AI Large Language Models in the post-pandemic era: ChatGPT and beyond. *Journal of University Teaching and Learning Practice*, *20*(2). https://doi.org/10.53761/1.20.02.07

Perkins, M., Furze, L., Roe, J., & MacVaugh, J. (2024). The Artificial Intelligence Assessment Scale (AIAS): A Framework for Ethical Integration of Generative AI in Educational Assessment. *Journal of University Teaching and Learning Practice*, *21*(06). https://doi.org/10.53761/q3azde36

QAA. (2023a). *Generative Artificial Intelligence in Education—QAA's response to DfE call for evidence*. https://doi.org/https://www.qaa.ac.uk/docs/qaa/news/generative-artificial-intelligence-call-for-evidence.pdf

QAA. (2023b). *QAA Academic Integrity Network Meeting*. QAA. https://www.qaa.ac.uk/docs/qaa/members/academic-integrity-network-meeting-march-2023.pdf?sfvrsn=758ab81_6

Rondini, S., Alvarez-Martin, C., Angermair-Barkai, P., Penacchio, O., Paz, M., Pelowski, M., Dediu, D., Rodriguez-Fornells, A., & Cerda-Company, X. (2026). Stable Diffusion Models Reveal a Persisting Human–AI Gap in Visual Creativity. *Advanced Science*, *13*(27), e24142. https://doi.org/10.1002/advs.202524142

Russel Group. (2023, July 3). *Principles on the use of generative AI tools in education | Russell Group*. Russel Group. https://www.russellgroup.ac.uk/policy/policy-briefings/principles-use-generative-ai-tools-education

Sarpong, J., & Adelekan, T. (2024). Globalisation and education equity: The impact of neoliberalism on universities' mission. *Policy Futures in Education*, *22*(6), 1114–1129. https://doi.org/10.1177/14782103231184657

SOAS. (n.d.). *SOAS statement on the use of generative artificial intelligence*. SOAS. Retrieved 12 June 2026, from https://www.soas.ac.uk/sites/default/files/2023-05/SOAS-statement-on-the-use-of-generative-artificial-intelligence.pdf

Stephenson, R., & Armstrong, C. (2026). *Student Generative AI Survey 2026*. Higher Education Policy Institute. https://www.hepi.ac.uk/wp-content/uploads/2026/03/HEPI-Report-199-Gen-AI-Survey-2026.pdf

Tao, Y., Finnerty, S., Robinson, S., Philpot, R., Shaw, H., & Levine, M. (2026). *Parenting or partnership? Corpus-assisted analysis of institution-people dynamics in university sustainability reporting*. Research Square. https://doi.org/10.21203/rs.3.rs-9518900/v1

Temper, M., Tjoa, S., & David, L. (2025). Higher Education Act for AI (HEAT-AI): A framework to regulate the usage of AI in higher education institutions. *Frontiers in Education*, *10*. https://doi.org/10.3389/feduc.2025.1505370

The University of East Anglia. (n.d.). *Generative AI Policy for Teaching and Learning*. The University of East Anglia. https://doi.org/https://assets.uea.ac.uk/f/185167/x/5558a0f812/generative-ai-policy-for-teaching-and-learning.pdf

Tsigaris, P., & Teixeira da Silva, J. A. (2026). AI detecting AI in academic writing: Why most AI detector findings are false. *Next Research*, *7*, 101396. https://doi.org/10.1016/j.nexres.2026.101396

UCU. (2026). *Principles for use ofartificial intelligence*. https://www.ucu.org.uk/media/15656/Principles-for-use-of-artificial-intelligence/pdf/UCU_AI_principles_March_26.pdf

University of Dundee. (2025). *AI (Artificial Intelligence) in Teaching and Assessment*. University of Dundee. https://www.dundee.ac.uk/guides/ai-artificial-intelligence-teaching-and-assessment

University of Edinburgh. (2025, July 23). *Using generative AI in your studies: Guidelines for students | Computing*. Information Services. https://information-services.ed.ac.uk/computing/comms-and-collab/elm/generative-ai-guidance-for-students/using-generative

Weber-Wulff, D., Anohina-Naumeca, A., Bjelobaba, S., Foltýnek, T., Guerrero-Dib, J., Popoola, O., Šigut, P., & Waddington, L. (2023). Testing of detection tools for AI-generated text. *International Journal for Educational Integrity*, *19*(1), 26. https://doi.org/10.1007/s40979-023-00146-z

Wilson, T. D. (2025). The development of policies on generative artificial intelligence in UK universities. *IFLA Journal*, *51*(3), 722–734. https://doi.org/10.1177/03400352251333796

Wu, J., Yang, S., Zhan, R., Yuan, Y., Chao, L. S., & Wong, D. F. (2025). A Survey on LLM-Generated Text Detection: Necessity, Methods, and Future Directions. *Computational Linguistics*, *51*(1), 275–338. https://doi.org/10.1162/coli_a_00549

Xiao, P., Chen, Y., & Bao, W. (2023). *Waiting, Banning, and Embracing: An Empirical Analysis of Adapting Policies for Generative AI in Higher Education* (arXiv:2305.18617). arXiv. https://doi.org/10.48550/arXiv.2305.18617

Xie, Q., Li, M., & Enkhtur, A. (2024). *Exploring Generative AI Policies in Higher Education: A Comparative Perspective from China, Japan, Mongolia, and the USA* (arXiv:2407.08986). arXiv. https://doi.org/10.48550/arXiv.2407.08986