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Generative Artificial Intelligence Policy: A Qualitative UNESCO Framework Analysis

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Abstract

Generative artificial intelligence's (GenAI) emergence has compelled higher education leadership to design robust policies that foster safe and responsible integration and promote academic integrity. However, there is a lack of knowledge and evaluation of how higher education institutions comprehensively regulate GenAI usage. This study employed a qualitative policy analysis technique to examine the GenAI policies of thirty (30) highly ranked universities according to the Quacquarelli Symonds (QS) ranking across the top ten countries for AI preparedness. UNESCO's eight-component GenAI framework served as a lens for evaluating the robustness of the policies. The study's findings reveal significant disparities in policy implementation. Specifically, although core ethical and governance principles are widely embraced, key issues like inclusion, equity, and sustainability, such as internet access, gender parity in AI, and environmental impact, are often overlooked. Nordic countries and New Zealand cover UNESCO's elements more fully than some higher-ranked AI Preparedness Index (AIPI) countries, indicating that AIPI ranking does not guarantee strong GenAI policies. Notably, no public policies were found for German universities and Tallinn University of Technology. The study underscores the necessity for higher education leaders to develop more inclusive and future-oriented policies that integrate social equity, interdisciplinary experimentation, and sustainability considerations. Future studies can replicate this research by focusing on the long-term impact of the policies on university operations such as assessment, teaching, learning, research, academic performance.

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Practitioner Notes

1. Universities and policymakers should strengthen GenAI policies to better promote inclusion, equity, and diversity.
2. Policymakers in education should adopt a more nuanced approach to developing GenAI competencies, focusing on gender inclusion and older workers' reskilling.
3. Higher education leadership should embed GenAI policy in long-term, intersectoral and interdisciplinary planning processes.

Keywords
Generative AI, artificial intelligence, GenAI policy, leadership, higher education.

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Introduction

The governance of higher education is pivotal to achieving quality, stability, equity, and overall effectiveness of education systems in an era where global higher education institutions are faced with uncertainties and transformation. This makes educational policy a fundamental component in higher education that provides an underlying framework guiding different structures. Higher education institutions respond to societal changes and reforms, such as advancements in technology, with policies to achieve their missions and visions. For example, the absence of a comprehensive, cohesive policy in integrating new technologies in education might have detrimental effects on pedagogical strategies and learning outcomes. Advanced digital technologies, such as artificial intelligence (AI), are accompanied by risks and opportunities that necessitate policy regulation (Chan, 2023; Tlili et al., 2023; UNESCO, 2023b). If school leadership wants to take advantage of the benefits of technology integration, there should be a consideration of policy-related components of the education system (UNESCO, 2023a). This means that successful education, especially in technology-enhanced learning environments, goes beyond the acquisition of technology to the strategic policies that govern its implementation. Additionally, outdated and poorly implemented technology policies inhibit meaningful technology use, the cultivation of digital literacy skills, and rapid engagement in learning (Adarkwah & Huang, 2023).

Policy itself has multifaceted meanings, but can be simply defined as the implicit or explicit identification of intentional courses of action being followed, or to be followed in addressing a specific problem or concern aimed at the accomplishment of some specified or desired set of outcomes (Harman, 1984). A policy, therefore, serves as a framework for institutions, such as higher education institutions, to operate consistently towards the achievement of established goals by offering guidance for the interplay between the organisational vision, values, processes, and actions. In essence, education policy deals with the “prescriptive regulation of flows of human resources, discourse and capital across educational systems towards normative social, economic and cultural ends” (Luke & Hogan, 2006, p. 1). Vergari (2015) considers education policies as essential for economic growth, social cohesion, democratic governance, and the general welfare of individuals and communities. In the context of AI, the formulation of sound and robust policies represents a valuable source of information on AI governance in terms of impacts, risks, and benefits (Schiff, 2022). Such education policies should grapple not only with the technology but also with its socio-political and moral dimensions. One key role of education leadership and teaching is the understanding of the design and aims of policies and their impacts and consequences (Jones, 2013).

Consequently, the role of higher education leadership in creating a strategic vision includes developing policies that support the effective integration of novel technologies for teaching, learning, research, and administrative tasks. Since generative artificial intelligence (GenAI) burst onto the scene, higher education leaders are being called upon to harness the potential of this groundbreaking technology without compromising academic integrity. By definition, GenAI refers to “computational techniques that generate new and meaningful content in the form of text, images, videos, or audio from training data” (Rasul et al., 2024, p. 2). Owing to the ethical dilemmas of GenAI integration, there has been hesitance and misapprehension by some educational leaders about its use (Wang et al., 2024). One popular educational case is the ban

on ChatGPT imposed by New York City and Los Angeles Unified educational institutions due to the risk of students cheating on assignments (The Guardian, 2023; Tlili et al., 2023). The drawbacks of using GenAI have compelled leaders of higher education institutions to explore measures for fostering responsible adoption of GenAI (McDonald et al., 2025; Rasul et al., 2024). Unsurprisingly, the internet is overrun with diverse advice on how to use GenAI and how to detect user cheating with the technology (McDonald et al., 2025). That is, the complexities surrounding GenAI make it essential for educational leaders to establish contextual and comprehensive education policies.

According to Hamerman et al. (2024), higher education leadership should implement policies that define clear guidelines for the use of GenAI while promoting and training faculty to effectively integrate GenAI into classroom assignments. Chan (2023) reiterates that there is an urgent necessity for university leaders to establish an AI education policy aimed at equipping students with the skills to work with and comprehend the principles of this technology. The speed of GenAI adoption and the slowness of policy development may gravely disrupt higher education (Crawford et al., 2023) and result in fragmented and varying policies, exposure to legal risks, ethical dilemmas, and uncertainties about the regulation of such tools. An example is the recent global survey conducted by UNESCO (United Nations Educational, Scientific and Cultural Organisation), involving over 450 universities and schools, which revealed that less than 10% have established formal policies or guidance regarding the use of GenAI applications (UNESCO, 2024). The UNESCO survey indicates a significant finding: institutions that reported having some form of guidance did not possess it in written form; instead, it was communicated verbally. Also, the report reveals that close to 20% of respondents were unsure whether their educational institutions had official GenAI policies or guidelines. This highlights the informal and adhoc nature of policy responses within the education sector.

Notwithstanding, in the policy adoption process among different institutions, a strategy that may seem rational for one institution may be irrational for others (Currie, 2012). Hence, having a normative reference helps ensure isomorphism by expediting the adoption of a policy for institutions in similar situations (e.g., exposure to GenAI). To build a common foundation for designing AI or GenAI policies, the UNESCO framework on GenAI is designed to provide comprehensive and uniform guidelines as a blueprint for all member states (UNESCO, 2023b). A recommendation is for university leaders to strive to ensure that their AI or GenAI policies keep pace with standards and practices across the nation and internationally (EDUCASE, 2024). The UNESCO GenAI policy guidelines for education and research offer this comprehensive international framework for all member states. Although not infallible, to some extent, the UNESCO framework serves as a valuable lens for critically evaluating the robustness and comprehensiveness of GenAI policies, particularly, socio-political and moral dimensions (contextualised as GenAI ethics), for its affiliate nations.

Specifically, the sociopolitical dimension deals with the social impact, normative principles of regulation (e.g., democracy, political autonomy, social justice: Erman & Furendal, 2022) and structural aspect of GenAI implementation involving privacy and data governance, surveillance, bias and discrimination, AI and employment, digital divide, and AI in governance (Wang et al., 2023), while moral dimensions typically involve questions about fundamental justice, moral rightness, freedom and so on (Erman & Furendal, 2022). Mak et al. (2025) assert that the sociopolitical context plays an integral role in institutional guidelines, such as universities

referencing local policy or legislation in their AI guidance to conform with normative principles and cultural norms. Additionally, research institutions have the moral obligation to ensure the oversight of AI (Bhaumik, 2025). Thus, GenAI ethics embodies both the duties of an AI application and its creators and underlying moral obligations (Laine et al., 2025). There is a need for a policy that tackles the social, political, and moral dimensions of AI implementation (Dg et al., 2020). The UNESCO framework is appropriate for this study because it covers both the socio-political and moral dimensions of GenAI use in education and research. Effective regulations should typically aim to strike a balance between protecting the public and promoting growth and innovation (Rosemann & Zhang, 2022). In the context of our study, higher education institutions with an effective ethical system should have policies that address core moral dimensions (e.g., issues of care, harm, fairness, or cheating: Bulla et al., 2025) and the social and political impacts of GenAI (Dg et al., 2020).

To this end, the current study employs the UNESCO GenAI policy framework as a lens to evaluate the GenAI policies of leading universities in UNESCO member states with high AI preparedness. Although GenAI originated in the mid-20th century (Turing, 1950), ChatGPT, introduced in 2022, “has emerged as a transformative force in higher education, offering both challenges and opportunities” (Farrelly & Baker, 2023, p. 1). Research, grading, and human-computer interaction could benefit from GenAI, while online testing security, plagiarism, job displacement, the digital literacy gap, and AI-induced anxiety could face risks. Due to its rapid expansion, regulation is needed (Dempere et al., 2023; Jin et al., 2024; Michel-Villarreal, 2023; Moorhouse et al., 2023). When GenAI technology emerged, universities increasingly worked on developing GenAI policies (An et al., 2025). In response to these regulations, since 2023, GenAI policy research in HEIs has increased.

The current study evaluates the GenAI policies of selected higher education institutions using UNESCO’s eight-component GenAI framework, adding a new research category. Such an approach can help provide a better understanding of how highly ranked universities are regulating GenAI beyond technological aspects and its broader implications for technological societies today in terms of ethical standards and norms. The analysis will focus on the highly ranked countries for AI preparedness, because for those countries characterised by “high AI exposure and strong foundational AI adoption preparedness … more emphasis should be placed on … adapting their legal and ethical frameworks to govern and foster AI advances” (Cazzaniga et al., 2024). As the “preparedness for AI-induced structural transformation will likely rely on the collective performance in all areas” (Cazzaniga et al., 2024, p. 21), such as the core areas of human capital, there is a need for universities to govern and foster AI. Additionally, this study will look at leading higher education institutions to guarantee they have GenAI policies, as a high academic reputation is linked to having these policies (Xiao et al., 2023). A fundamental issue of concern is the lack of knowledge of how leading higher education institutions comprehensively regulate GenAI usage in nations with high AI preparedness. The aim of the research is to gain insights into the status quo of the GenAI policy development among leading universities in countries with high AI exposure by evaluating their policies. Policy analysis prompts the derivation of recommendations for policy development. The research question of the current study is:

Research Question 1. How do leading universities in nations with high AI preparedness comprehensively address the socio-political and moral dimensions of their GenAI policies from the perspective of the UNESCO GenAI policy framework?

To support the research question, three sub-questions are proposed:

Sub Research Question 1. What are the characteristics of GenAI policies across selected universities in light of socio-political and moral considerations?

Sub Research Question 2. What key components of GenAI policies at leading universities reflect socio-political and moral considerations according to the UNESCO GenAI policy framework?

Sub Research Question 3. To what extent do policies vary across countries/regions in the context of socio-political and moral considerations?

In the current study, this framework will be utilised to describe and evaluate the GenAI policies in higher education. The proposed eight specific measures that are operationalised using a kind of indicators serve as criteria for planning the policies (UNESCO, 2023b, p. 24).

Literature

GenAI Policy Availability Studies

Early studies on institutional responses to GenAI in higher education primarily examined whether universities had published any public guidance or policy at all. Xiao et al. (2023), analysing the top 500 universities in the 2022 QS World University Rankings, reported that fewer than one-third had introduced ChatGPT-related policies at the time of data collection (i.e., less than 30%). Less than 30% of the top 500 QS World University Ranking universities in 2022 had policies (Xiao et al., 2023). Their analysis also showed that policy availability was positively associated with academic reputation, measured by QS World University Rankings, location in English-speaking countries, and public sentiment/public attention to ChatGPT as approximated through Google Trends indicators of keyword searches for ChatGPT (Xiao et al., 2023). Following Xiao et al. (2023), academic reputation, measured by QS World University Rankings, location in an English-speaking country, and public sentiment measured by Google trend metrics of the keyword searches for ChatGPT (Xiao et al., 2023) were positively correlated with ChatGPT policies.

Subsequent studies reported substantially higher rates of publicly available guidance, but these differences should be interpreted in relation to sampling frames, timing, and definitional scope. Moorhouse et al. (2023), focusing on assessment-related guidelines among the Times Higher Education World University Rankings 2023 top 50 universities, found that under 50% had published relevant guidance. In contrast, Ullah et al. (2024), examining the top 50 QS-ranked universities, reported that 82% had publicly available GenAI-related guidelines/policies, while An et al. (2025), focusing on the top 50 U.S. universities, found an even higher prevalence of faculty guidance (94%). Rather than indicating inconsistency across the literature, these figures

collectively point to a rapidly evolving policy landscape in which institutional responses expanded quickly after the public release of ChatGPT.

Taken together, availability studies provide important evidence that higher education institutions increasingly recognise the urgency of institutional guidance, and that academic reputation seems to positively interact with policy availability. Universities are increasingly recognising the urgency for policy development, and academic reputation seems to positively interact with policy availability. However, the existence of a policy document does not in itself indicate pedagogical adequacy, implementation readiness, or institutional capacity for assurance. This limitation motivates closer analysis of policy content and governance mechanisms.

GenAI Policy Content Studies

Subsequent research on GenAI has moved beyond policy presence to examine policy content. Across studies, recurring themes include academic integrity, responsible use, ethics, and institutional risk management. An et al. (2025) found four topics in the GenAI guidelines of the top 50 U.S. universities: integration of GenAI in learning and assessment, GenAI in visual and multimodal media, security and ethical considerations in GenAI, and GenAI in academic integrity (An et al., 2025). Similarly, Ullah et al. (2024) showed that university GenAI guidelines emphasise ethics and responsible usage while McDonald et al. (2025) identified that the majority of U.S. universities classified as Research 1 encouraged GenAI use, often accompanied by guidance for classroom practice.

At the same time, critical work suggests that policy discourse may be overly anchored in misconduct prevention and “originality” concerns, especially in relation to assessment. Luo (2024), in a critical review of policy responses in leading universities, argues that many policies frame GenAI primarily as a threat to the originality of students’ work, thereby narrowing the pedagogical debate. Dabis and Csáki (2024), examining policy responses in leading universities, likewise highlight the centrality of ethical concerns but also point to the need for more nuanced institutional responses beyond prohibition-oriented framing. Extending these critiques with a more differentiated institutional view, Loku et al. (2024) found similarly distributed profiles among top-ranked universities based on a latent profile analysis for acceptance and institutional factors along with an analysis of public universities’ documents by ChatGPT: Profile 1 universities have high international student ratios and research output and strongly oppose unauthorized use, while profile 2 universities promote safe GenAI use with lower international presence and research output (Ioku et al., 2024). Profile 3 universities have a high international presence but low research output, while profile 4 universities have excellent academic reputations and research output but modest international presence and lower faculty-student ratios. In a similar study, Xiao et al. (2023) investigated ChatGPT allowance correlations. Lower-ranked universities are more likely to prohibit ChatGPT. Moreover, the faculty-student ratio, citations, and English-speaking countries positively affect ChatGPT prohibition, while the number of peer universities that prohibit ChatGPT is negatively connected (Xiao et al., 2023).

Cross-national comparative analyses further suggest that policy orientations are also shaped by broader governance cultures and national policy environments. A recent study of policy

documents from 110 universities in China, Japan, and the U.S. by Li et al. (2025) shows "varying levels of self-efficacy in how universities approach Generative AI integration" (Li et al., 2025, p. 23): While the U.S. universities employ "a pragmatic and flexible approach" characterised by "faculty autonomy, practical application, and policy adaptability," Japanese universities follow a "government-regulated approach" that emphasises ethics and risk management within a normative frame of human-centeredness (Li et al., 2025). Chinese universities follow a "centralised, government-led model" that prioritises technology application over early policy development (Li et al., 2025). The nation's politics and university reputation seem to influence the approach and the GenAI's acceptance.

This body of work significantly advances current knowledge by showing that universities are not simply "for" or "against" GenAI; rather, they are developing heterogeneous policy repertoires that blend permission, restriction, and conditional use, and that these repertoires vary systematically with institutional characteristics (e.g., internationalisation, research output, ranking position) and broader governance contexts. However, much of this literature still focuses on declarative content (what policies say) rather than operational assurance (how policy commitments are enacted, monitored, updated, and supported in learning and teaching practice).

GenAI Policy Studies for Specific Groups or Topics

Dabis and Csáki (2024) analysed GenAI ethics at 30 Shanghai Ranking top 500 universities. As a main ethical rule, they identified that student assignments must represent the acquired individual knowledge. Luo (2024) found that the main problem in 20 world-leading universities' policy guidelines is that students are not allowed to submit original work for assessment. The policy's main issue is student plagiarism in assessments.

Jin et al. (2025, p. 1) complain about the GenAI adoption strategies in higher education across 40 universities from six global regions, noting that the "gaps remain in comprehensive policy frameworks..." Additionally, Ullah et al. (2024) state that the guidelines inadequately address educational needs. This review found a lack of knowledge about how higher education institutions comprehensively regulate GenAI usage. That makes it difficult for higher education institutions to address GenAI issues, risks, and opportunities (Chan, 2023; Luo, 2024).

GenAI in Higher Education

GenAI has rapidly become a distinct field of inquiry within higher education rather than merely an extension of earlier educational technology debates. Recent reviews suggest that the literature is increasingly organised around several recurring themes, including pedagogical applications in teaching and learning, curriculum development, student and faculty perceptions, assessment redesign, academic integrity, and institutional support for responsible use (Tillmanns et al., 2025; Wu et al., 2025). This indicates that GenAI is no longer treated as a marginal or experimental issue, but as a structural challenge and opportunity affecting core university functions.

The literature generally presents GenAI as offering both important educational affordances and significant risks. On the positive side, studies emphasise its potential to support personalised learning, idea generation, rapid feedback, writing assistance, and increased efficiency for both students and instructors (Tillmanns et al., 2025; Wu et al., 2025). At the same time, scholars consistently point to risks such as hallucination, bias, misinformation, superficial learning, overreliance, and the possible erosion of independent academic work (Lye, 2024; Miao & Holmes, 2023). As a result, current scholarship tends not to frame GenAI as either inherently beneficial or inherently harmful; instead, its educational value is seen as dependent on how effectively institutions redesign learning, teaching, and support structures around its presence (Tillmanns et al., 2025; Miao & Holmes, 2023).

A particularly prominent theme in this literature is assessment. GenAI has challenged traditional assumptions about authorship, originality, and the validity of unsupervised written coursework, leading many scholars to argue that conventional assessment formats are increasingly vulnerable in the GenAI era (Lye, 2024). Rather than recommending outright prohibition, however, much of the recent literature advocates assessment redesign through more authentic, process-based, multimodal, and supervised approaches that better reflect the realities of AI-mediated learning (Lye, 2024; Khlaif et al., 2025). In this sense, GenAI is not only a misconduct issue; it is also prompting a broader reconsideration of what assessment in higher education is intended to measure (Department for Science, Innovation and Technology, 2024).

Overall, the higher education literature suggests that the central question is no longer whether GenAI will be used, but how universities can respond in pedagogically meaningful, ethically robust, and institutionally sustainable ways. The strongest contributions therefore move beyond simple adoption narratives and instead locate GenAI within wider debates about academic integrity, AI literacy, curriculum redesign, staff capability, and the future purposes of higher education itself (Tillmanns et al., 2025; Wu et al., 2025).

GenAI Attempts at Policy and Assurance

Alongside the growing research on GenAI usage in higher education, there has also been a focus on institutional and regulatory responses. A useful distinction in this literature is between policy and assurance. Policy generally refers to rules, expectations, and guidance concerning acceptable and unacceptable uses of GenAI, whereas assurance refers more specifically to the processes through which organisations measure, evaluate, and communicate whether AI systems are trustworthy, safe, and aligned with relevant standards and institutional values (UK Government, 2024). In other words, policy sets intentions and boundaries, while assurance is concerned with demonstrating that these intentions are being implemented credibly in practice.

The literature suggests that policy responses are expanding, but remain fragmented. OECD analysis of 18 countries and jurisdictions found that, as of early 2024, none had introduced specific regulation on GenAI in education, while many relied instead on non-binding guidance and locally developed institutional responses (OECD, 2023). UNESCO similarly argues that the rapid release of public GenAI tools has outpaced the adaptation of national regulatory frameworks, leaving educational institutions underprepared to validate such tools and users insufficiently protected in relation to privacy and oversight (Miao & Holmes, 2023). These

findings support the view that policy development is active, but uneven and incomplete across systems.

This fragmentation is also visible at the university level. Comparative analysis of 343 university AI policies across Australia, Canada, China, the United Kingdom, and the United States found substantial variation in institutional approaches, including differences in instructor discretion, disclosure requirements, and the extent to which GenAI is framed as a matter of academic integrity (Parker, 2025). Such evidence suggests that universities are not converging around a single governance model; instead, they are producing diverse and locally specific responses shaped by national, disciplinary, and organisational contexts.

By contrast, assurance in higher education appears less developed than policy. Cross-sector frameworks such as the “NIST Generative AI Profile” provide important guidance on risk management for issues such as confabulation, harmful bias, privacy, and information integrity (NIST, 2024). However, these frameworks are broad and not designed specifically for higher education. In the higher education sector itself, bodies such as Quality Assurance Agency for Higher Education, Tertiary Education Quality and Standards Agency, and European Association for Quality Assurance in Higher Education have begun to respond through guidance, toolkits, and principles-based resources, but these remain largely advisory rather than binding assurance systems (QAA, 2024; TEQSA, 2024; ENQA, 2025). This means that while policy guidance is proliferating, assurance mechanisms in higher education are still emerging, relatively soft in form, and unevenly institutionalised.

Taken together, the literature supports a clear conclusion: attempts at GenAI policy in higher education are increasing, but they remain fragmented across jurisdictions and institutions, while assurance mechanisms are still comparatively immature. A major gap in the field, therefore, is not simply whether universities have GenAI policies, but whether they possess robust, transparent, and evidence-based assurance arrangements capable of sustaining trust in teaching, learning, assessment, and academic standards (OECD, 2023; UK Government, 2024; ENQA, 2025).

Theoretical Framework

In recent years, GenAI frameworks or principles for higher education organisations, such as those introduced by Chan (2023), UNESCO (2023b), OECD (2023), and the U.K.’s Russell Group (2023), have been introduced. While OECD (2023) developed a discussion paper on AI in education and the Russell Group has established principles for a consortium of universities, the Russell Group, to guide the use of GenAI in higher education, UNESCO (2023b) has proposed a detailed framework that is intended to support the appropriate, responsible and ethical use of GenAI in education and research. Referring to the analysis of a survey with 457 students and 180 teachers and staff from different disciplines in Hong Kong universities, Chan (2023) examined the requirements, guidelines and strategies necessary for developing AI policies for university teaching and learning. UNESCO’s GenAI guidance is built on a human-centred and rights-oriented approach and frames GenAI governance as a question of public accountability, equity, and protection of human agency. Table 1 summarises UNESCO’s eight policy elements, which collectively function as a normative “governance architecture”: (1)

inclusion and cultural-linguistic diversity; (2) human agency; (3) monitoring and validation; (4) learner competencies; (5) educator and researcher capacity; (6) pluralism and epistemic diversity; (7) local experimentation and evidence accumulation; and (8) long-term, interdisciplinary and intersectoral review. These elements extend beyond academic integrity concerns and position GenAI as a socio-technical system requiring sustained oversight across the technology and policy life cycle.

UNESCO's framework offers three concise strengths for evaluating institutional GenAI policy. First, it highlights equity risks arising from unequal access and skewed training data. Secondly, it frames governance as an ongoing process through monitoring and validation of bias and harmful outputs. Lastly, it foregrounds epistemic risks (e.g., unreliable outputs and reduced pluralism), linking GenAI governance to pedagogical quality rather than only misconduct prevention (UNESCO, 2023b).

Table 1

Framework for GenAI Use in Education and Research (UNESCO, 2023b)

No.	Policy Element	Exemplar Indicator
1	Promote inclusion, equity, and linguistic and cultural diversity	- Take action to promote universal internet connectivity and enhance human agency.
2	Protect human agency	- Make learners aware of GenAI use of their data.
3	Monitor and validate GenAI systems for education	- Build mechanisms to ensure GenAI is bias-free.
4	Develop AI competencies including GenAI-related skills for learners	- Develop AI curricula for different educational levels and foster creative use.
5	Build capacity for teachers and researchers to make proper use of GenAI	- Adjust guidance for navigating GenAI tools for researchers and teachers.
6	Promote plural opinions and plural expressions of ideas	- Understanding GenAI is fast but can often provide unreliable information.
7	Test locally relevant application models and build a cumulative evidence base	- Strategically plan GenAI design and adoption.
8	Review long-term implications in an intersectoral and interdisciplinary manner	- Multi-stakeholder collaboration to mitigate GenAI risks.

At the same time, the framework exposes a key implementation gap. While Table 1 provides exemplar indicators (e.g., "bias-free" mechanisms; learner awareness of data use), these are illustrative rather than enforceable and rarely specify measurable validation criteria, audit routines, procurement requirements, or clear accountability. UNESCO also notes limited institutional readiness for validation and educator capacity-building, suggesting that human-centred commitments may remain rhetorical unless converted into operational infrastructure (UNESCO, 2023b).

Accordingly, in this research, UNESCO is referred to as "a global leader in education," which introduced general guidance for GenAI in education and research through a "human-centred approach" (UNESCO, 2023b) and -as an evaluative lens to analyse university GenAI policies at

two levels: (a) declarative alignment (which UNESCO elements are addressed), and (b) operational assurance (whether policies define actionable mechanisms, responsibilities, and review structures that can realistically enact those commitments in higher education practice).

Method

The current study adopts a comprehensive qualitative evaluation approach that involves describing, analysing, and evaluating policies. This method was appropriate for the study because it helps to explore, qualitatively, the knowledge, assumptions, experiences, and values of individuals and groups within the educational landscape to derive and construct meaning about policy (Maher, 2025). Qualitative methods such as interviews and document analysis are recommended approaches to higher education policy analysis (Gibton, 2015; Owen, 2014). In the context of this study, policy documents of selected higher education institutions were the unit of analysis. This approach is efficient and manageable when policy documents are available of policy documents, and there is no need to collect data from human participants (Cardno, 2018). Cardno states that the analysis of policy documents is regarded as an appealing qualitative research method.

Research Design

The study utilised a policy analysis method to provide a comprehensive overview of GenAI implementation at selected world-class universities. Policy analysis is defined as “the process of systematic investigation of the implementation and impact of existing policy (ex-post analysis), and of options for new policy (ex-ante analysis)” (Milovanovitch, 2018, p. 7). Policy analysis provides various ways and tools to generate and transform information relevant to policy to facilitate its evolution to tackle social problems (Yang et al., 2023). This method is appropriate for this study because it aims to analyse GenAI policies of leading universities regarding GenAI regulation.

Sample

A purposive sampling strategy was adopted to include high-impact institutions actively engaged in AI governance. This means that a deliberate process/predetermined criteria were followed to select countries and higher education institutions within the countries that share specific qualities to gain a thorough understanding of the investigated phenomenon (Creswell & Poth, 2018). First, the top ten countries for AI preparedness were selected based on the International Monetary Fund’s AI Preparedness Index (IMF, 2023), as visualised by Visual Capitalist (Zhu, 2024). This index, covering 174 countries, aggregates data from eight major international organisations, including the International Labour Organisation, World Bank, and World Economic Forum. Second, university rankings were used to select higher education institutions from the countries.

University rankings function as a policy instrument that governments and institutional leaders use to underpin and quicken higher-education reforms (Hazelkorn, 2008). Comparative analyses of national ranking systems show that these rankings inform strategic choices and public policy questions, positioning highly ranked institutions as reference models for

governance and quality (Dill & Soo, 2005). Empirical evaluations of targeted excellence initiatives further indicate that investing in a small set of leading universities can yield broader, system-level effects, not only within the focal institutions but across the higher-education ecosystem (Lovakov et al., 2021). In the specific case of Russia's Project 5–100, participation produced a significant positive effect on quantitative research performance, illustrating how top-tier institutions can pull national outputs upward and thereby lead the system (Matveeva et al., 2021). Taken together, these findings substantiate the claim that top-ranked universities lead their countries by setting benchmarks that both guide policy and elevate sector performance.

Table 2

The Highest Ranked Universities from the 10 Highly AI-Prepared Countries

Country	University 1	University 2	University 3
Netherlands	Delft University of Technology (TU Delft)	University of Amsterdam (UvA)	Utrecht University (UU)
Germany	Technical University of Munich (TUM)	Ludwig-Maximilians-Universität München (LMU Munich)	Universität Heidelberg (Heidelberg)
Sweden	Royal Institute of Technology (KTH)	Lund University (Lund)	Uppsala University (Uppsala)
Switzerland	Eidgenössische Technische Hochschule Zürich (ETH Zurich)	École Polytechnique Fédérale de Lausanne (EPFL)	University of Zurich (UZH)
USA	Massachusetts Institute of Technology (MIT)	Harvard University (Harvard)	Stanford University (Stanford)
Singapore	National University of Singapore (NUS)	Nanyang Technological University (NTU)	Singapore University of Technology and Design (SUTD)
Denmark	University of Copenhagen (UCPH)	Technical University of Denmark (DTU)	Aarhus University (Aarhus)
Estonia	University of Tartu (Tartu)	Tallinn University of Technology (TalTech)	Tallinn University (Tallinn)
Finland	Aalto University (Aalto)	University of Helsinki (Helsinki)	Lappeenranta University of Technology (LUT)
New Zealand	The University of Auckland (Auckland)	The University of Otago (Otago)	Massey University (Massey)

Accordingly, from each of the selected countries, three world-class universities were chosen using the 2024 Quacquarelli Symonds (QS) global rankings, which assess institutions on criteria such as academic reputation, research output, teaching quality, employer feedback, and student demographics (Rybiński & Wodecki, 2022). Although 30 universities were initially targeted, four were excluded due to the absence of publicly accessible GenAI policies. As a result, 26 universities were included in the final analysis (Table 2).

Search Strategy

The search was conducted using the Google search engine as the primary tool for locating relevant policies.

Table 3

Inclusion/Exclusion Criteria for GenAI Policy Analysis

Criteria type	Inclusion criteria	Exclusion Criteria
Policy type	Policies related to GenAI	General AI policies not related to GenAI
Geographical focus	Policies from universities in Singapore, Denmark, the US, Netherlands, Estonia, Finland, Switzerland, New Zealand, Germany, and Sweden	Policies from universities outside the specified countries
Institution type	Policies from the top three world-class universities per the QS global rankings	Policies from universities ranked outside the top three per the QS global rankings
Level of applicability	Institutional-level GenAI policies	Departmental/faculty-level GenAI policies and all non-institutional level GenAI policies
Publication date	Policies published/revised within the last five years	Policies older than five years
Content relevance	Policies addressing the eight specified elements in the UNESCO GenAI policy framework	Policies not addressing any of the eight elements of the UNESCO GenAI policy framework
Language	Policies available in English or the primary language of the country	Policies not available in English or the primary language
Accessibility	Policies that are publicly accessible online	Policies that are not publicly available online

Initially, the researchers identified keywords commonly used in national AI strategies, academic literature, and by international organisations engaging with Generative AI (GenAI). Five main keywords were used to guide the search: “AI”, “GenAI,” “Policy,” “Regulation,” and “Guidelines.” The researchers used various combinations of these terms, particularly “AI” or “GenAI” AND “Policy” or “Regulation” or “Guidelines.”

To find policies specific to individual universities, the name of the university was added to the search string (e.g., AI policy/guidelines or GenAI policy/guidelines + [University Name]). The primary sources used to retrieve these policies included: official university websites, press releases or news articles published by the universities, and the websites of the Ministry of Education (MoE) of the respective countries. All selected university websites were systematically searched to ensure that any available GenAI-related policy documents were retrieved. Table 3 demonstrates the inclusion and exclusion criteria for selecting GenAI policies.

Data Collection

Data collection was conducted over a 4-month period, between October 2024 and January 2025. The analytical framework was informed by the Cambridge Dictionary’s definition of "policy": "a set of ideas or a plan of what to do in particular situations that have been officially agreed upon by a group, business organisation, government, or political party" (Cambridge Dictionary, n.d.).

For each of the selected universities, researchers systematically reviewed official university websites to locate open-access, institution-wide GenAI policy documents or related materials. In cases where policy information was missing or limited, an email inquiry was sent to official university contacts to verify the existence of a GenAI policy. That is, the researchers collected official institutional policies publicised to govern GenAI integration for all university operations and not limited to the classroom or beyond the classroom and without being restricted to any specific target group within the university. This is because the educational environment is a complex system with several interconnected subsystems and stakeholders, where any decision made on a single component or level has a spillover effect on other components and subsystems (UNESCO, n.d.). The system perspective demands that policy and decision-makers design coherent and consistent educational policy and strategic frameworks. Additionally, this approach helped in providing a comprehensive understanding of the integration of GenAI across diverse university sectors. In cases where policy information was missing or limited, an email inquiry was sent to official university contacts to verify the existence of a GenAI policy. Departmental or faculty-level policies were excluded to maintain comparability and institutional scope. For all the policies collected, the publication and revision dates were noted where available to assess the currency of each policy.

A total of 159 documents, including policy texts, institutional announcements, webpages, and supporting materials, were retrieved and reviewed. Most of the universities published their policies on web pages along with a report document, while some universities only had either one of them. Specifically, 18 universities (69.2%) had their policies only as website publications, one university (3.8%), which is the National University of Singapore, had its policy only in a report form, and seven universities (26.9%) had their policies as both website and report publications. For example, the University of Amsterdam and Stanford University had multiple policies in the form of websites and report documents, while Aarhus University, Massachusetts Institute of Technology (MIT), and KTH Royal Institute of Technology each had multiple policies in the form of only website publications. The UNESCO policy framework used as the standard metric for evaluating all the policies ensures equal comparability (a balanced treatment of the data obtained), irrespective of the volume of policy publications of universities. The qualitative analysis focused on the content and not the number of policies to ensure institutions with lower volume of publications were adequately covered to reflect the overall trends across all institutions. While the search may not have captured all possible public policies, the researchers mitigated this limitation through iterative searches and dual-author consensus review to ensure comprehensiveness and reliability of the final dataset.

Measures

The current study integrates (1) the UNESCO GenAI policy framework (2023b), including its indicators as a normative reference, (2) the AI Preparedness Index (AIPI) to select countries with high AI exposure, and (3) the QS ranking to identify leading universities. The AIPI was proposed by the International Monetary Fund (IMF) in 2023. This index refers to strategic areas and evaluates AI preparedness in 174 countries (Cazzaniga et al., 2024, p. 20). The macro-structural indicators of AI adoption of AIPI are classified under the four categories: (1) digital infrastructure, (2) innovation and economic integration, (3) human capital and labour market policies, and (4) regulation and ethics (Cazzaniga et al., 2024). Averaging the set of sub-

indicators for each of the four dimensions leads to average measure of the AIPI (Cazzaniga et al., 2024). The countries are selected using AIPI.

Document Analysis

The policy analysis followed the four-step guide on policy analysis by the European Training Foundation (Milovanovitch, 2018). This involves framing and understanding the problem, collecting and describing the evidence, and interpreting the evidence, and formulating recommendations, and outlining the options.

The first step is *framing and understanding the problem*. It was identified from the literature review as a lack of knowledge and evaluation of how higher education institutions comprehensively regulate GenAI usage, which makes it difficult for higher education institutions to address GenAI regulation. The analysis also looked at the different stages of policy implementation by universities in the same country. A key challenge for leading higher education institutions is the lack of comprehensive guidelines to ensure the successful implementation of GenAI (Dai et al., 2024; Luo, 2024; Zlotnikov et al., 2025).

The second step is *collecting and describing the evidence*. In this study, all available university public policies on GenAI were collected and described using the UNESCO policy framework on GenAI for education and research. The framework lists eight (8) key elements with sub-indicators briefly described to guide the analysis. In this stage, a content analysis approach was applied. Content analysis offers a structured and objective approach to make valid conclusions from verbal, visual, or written data to enable researchers to describe and quantify specific phenomena" (Downe-Wamboldt, 1992). An open coding approach was employed where the researchers read the textual data line-by-line and compared it to descriptions in the UNESCO GenAI policy framework. Two researchers independently analysed policies in two countries (six universities in total) and later met to compare their analyses. After consensus was reached, the whole research team met again to discuss the analysis from individual teams to reach a broader consensus for all the analysed policies.

The third step involves *interpreting the evidence*. In this stage, inferences were drawn from the reviewed literature and insights from the UNESCO GenAI policy framework. The interpretations were made in response to the questions raised during the problem framing, as recommended by Milovanovitch (2018). The evidence was first described to paint a general picture of GenAI policy implementation at the leading universities before any interpretation to ensure the right judgement was made. A detailed interpretation of the evidence is presented in the discussion section. In the discussion, an indicator for a specific policy element was considered neglected if it was addressed by five or fewer universities.

The final step involves *formulating recommendations and outlining the options*. In the concluding sections, it was recommended that actionable strategies that higher education institutions, especially world-class universities in countries known for AI preparedness, should undertake to promote a cautious, safe, and effective approach to GenAI use and implementation.

Code Comparison

To ensure intercoder reliability, the websites were evenly distributed among four researchers and initially subjected to pairwise cross-checking. Webpages deemed suitable to be classified as AI policy were then reviewed collectively by all four coders. The final coding process continued until agreement among at least three researchers was achieved, with the process completed by January 2025. After the second round of cross-checking, 100 websites remained eligible for analysis. Of these, four were initially marked as “suitable” by three coders and another four by two coders; however, after team discussions, all eight reached full consensus among all four coders. Additionally, one item was initially rated as “not suitable” by three coders, but following further deliberation, full agreement was reached, and the item was ultimately included in the final analysis. In the final stage, policy-related qualitative websites were analysed through pairwise coder comparisons, adhering to the UNESCO framework. Discussions were conducted until reaching full consistency among all four coders regarding which sentences corresponded to specific elements and indicators, culminating in the final analytical outcomes.

Results

In the following section, the findings are presented in accordance with each research question, allowing for a structured analysis and a clear alignment between the questions posed and the results obtained.

Characteristics of GenAI Policies

Policies appear in various formats, including website publications and formal reports (Table 4). Out of the 26 universities with official GenAI policies, only institutional-level policies were included in this analysis, while departmental-level policies were excluded to ensure consistency and comparability across universities. 70.0% of the universities are in the implementation phase, actively integrating GenAI policies through structured procedures, training, and enforcement. Approximately 18.0% are piloting, characterised by limited-scale testing of policy elements, often within selected departments or courses, to assess feasibility before institution-wide adoption. The remaining 2.0% have no policy. Out of the 26 universities with official GenAI policies, 12 (46.2%) categorise their policy as belonging to both the AI and GenAI categories, while 15 (57.7%) consider GenAI as a standalone category. That is, a majority of the universities prefer categorising GenAI independently. While some universities adapted/implemented their AI policy guidelines to incorporate GenAI, other universities designed policies specifically focusing on GenAI. Most policies emphasise guiding students on the responsible use of GenAI tools, often also covering multiple aspects of AI use in teaching, assessment, and research, reflecting a fair commitment to moral standards of ethical conduct. The GenAI policies of only two universities were categorically stated as being influenced by broader socio-political guidelines, reflecting less alignment with socio-political frameworks. The University of Helsinki in Finland stated its GenAI policy is also governed by the ethical guidelines set by the European Commission, and the University of Otago in New Zealand mentioned its GenAI policy is governed by a national AI policy framework. Universities in New Zealand and Denmark have multiple policies, while Germany and Estonia’s TalTech lack official, publicly available ones. Additionally, 42.0% of the policies have recent revisions, and 80.0% are

institutional-level, with approximately 7.0% of universities adopting national or continental policies.

Table 4

Characteristics of GenAI Policies Across Selected Universities

Focus and Status	University
Implementation of AI and GenAI	TU Delft, UvA, Uppsala, UZH, NUS, UCPH, Aarhus, Tallinn Uni., Aalto, Helsinki, LUT, Massey
Implementation of Only GenAI	UU, KTH, ETH Zurich, EPFL, MIT, Harvard, Stanford, NTU, SUTD, DTU
Piloting of AI and GenAI	Lund
Piloting of Only GenAI	Tartu, Auckland, Otago

Key Components of GenAI Policies

Table 5 and Figure 1 reflect the extent to which these elements are incorporated, highlighting both common inclusions and gaps.

Table 5

GenAI Policy Elements at Leading Universities - UNESCO (2023b) Framework

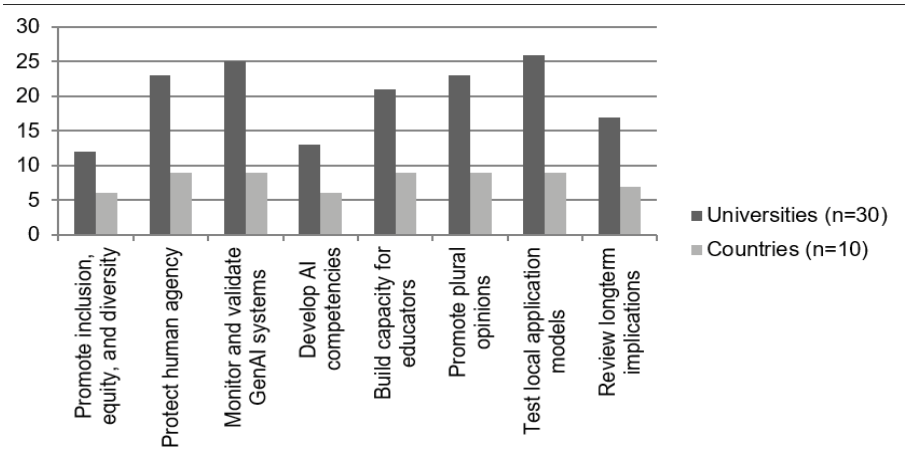
		Element 1	Element 2	Element 3	Element 4	Element 5	Element 6	Element 7	Element 8
NL	TU Delft	✗	✗	✔	✗	✗	✗	✔	✔
	UvA	✗	✔	✔	✗	✔	✔	✔	✔
	UU	✗	✔	✔	✗	✔	✗	✔	✔
DE	TUM	–	–	–	–	–	–	–	–
	LMU Munich	–	–	–	–	–	–	–	–
	Heidelberg	–	–	–	–	–	–	–	–
SE	KTH	✔	✔	✔	✔	✔	✔	✔	✔
	Lund	✔	✔	✔	✔	✔	✔	✔	✔
	Uppsala	✔	✔	✔	✔	✔	✔	✔	✔
CH	ETH Zurich	✗	✔	✔	✔	✔	✔	✔	✗
	EPFL	✗	✔	✔	✗	✗	✔	✔	✗
	UZH	✔	✔	✔	✔	✔	✔	✔	✗
US	MIT	✗	✔	✗	✗	✗	✔	✔	✗
	Harvard	✗	✔	✔	✗	✔	✔	✔	✔
	Stanford	✗	✗	✔	✗	✗	✗	✔	✔
SG	NUS	✗	✔	✔	✗	✔	✔	✔	✔
	NTU	✗	✗	✔	✗	✗	✔	✔	✗
	SUTD	✗	✔	✔	✗	✔	✔	✔	✔
DK	UCPH	✔	✔	✔	✗	✔	✔	✔	✔
	DTU	✗	✔	✔	✔	✔	✔	✔	✔
	Aarhus	✗	✔	✔	✔	✔	✔	✔	✔
EE	Tartu	✔	✔	✔	✔	✔	✔	✔	✗
	TalTech	–	–	–	–	–	–	–	–
	Tallinn Univ.	✔	✔	✔	✗	✔	✔	✔	✗
FI	Aalto	✔	✔	✔	✗	✔	✔	✔	✔

		Element 1	Element 2	Element 3	Element 4	Element 5	Element 6	Element 7	Element 8
	Helsinki	✔	✔	✔	✔	✔	✔	✔	✔
	LUT	✔	✔	✔	✔	✔	✔	✔	✔
NZ	Auckland	✔	✔	✔	✔	✔	✔	✔	✔
	Otago	✔	✔	✔	✔	✔	✔	✔	✔
	Massey	✗	✔	✔	✔	✔	✔	✔	✗

Element 1: Promote inclusion, equity, and linguistic and cultural diversity, **Element 2**: Protect human agency, **Element 3**: Monitor and validate GenAI systems for education, **Element 4**: Develop AI competencies including GenAI-related skills for learners**, Element 5**: Build capacity for teachers and researchers to make proper use of GenAI, **Element 6**: Promote plural opinions and plural expressions of ideas, **Element 7**: Test locally relevant application models and build a cumulative evidence base, **Element 8**: Review long-term implications in an intersectoral and interdisciplinary manner

Figure 1

Elements Across the Universities and Countries



The first element of the framework, promoting inclusion, equity, and diversity, comprises three indicators (Table 1) to ensure that GenAI tools are accessible to all while fostering equity, linguistic diversity, and cultural pluralism. An analysis of 10 countries and 30 universities shows that 40.0% (*n* = 12) of the universities and 60.0% (*n* = 6) of the countries implemented at least one of these indicators, making this the least emphasised component of the framework, indicating a significant gap in attention to inclusion in GenAI adoption. The three indicators of the element are adopted by 13.3% (*n* = 4), 23.3% (*n* = 7), and 30.0% (*n* = 9) of the universities, as well as 30.0% (*n* = 3), 30.0% (*n* = 3) and 50.0% (*n* = 5) of the countries (Fig. 2), respectively, indicating a somewhat balanced distribution. Sweden, Finland, Estonia, and New Zealand stand out, as nearly all their selected universities include this element, demonstrating a commitment to inclusion (Fig. 3). KTH (2024a), for instance, covers all indicators of the element by questioning how to ensure accessibility to everyone, by making sure that AI does not discriminate or exclude people, and by giving students the choice to opt out of using AI. However, there is no clear pattern in these findings, as strong implementation is scattered across a mix of regions and countries without a cohesive trend.

Figure 2

Adoption of the First Element

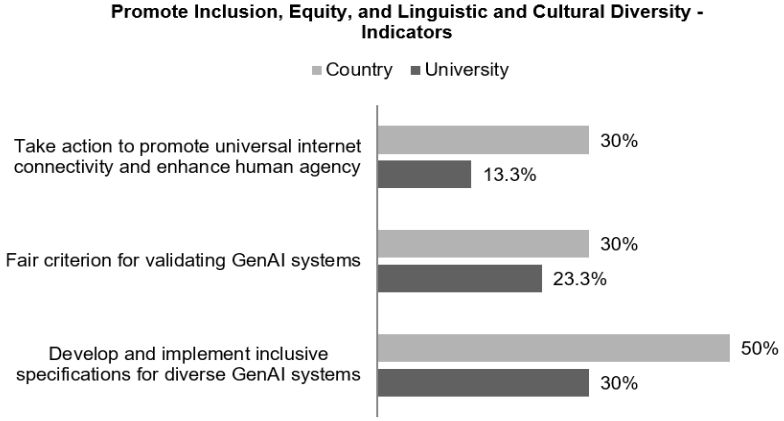
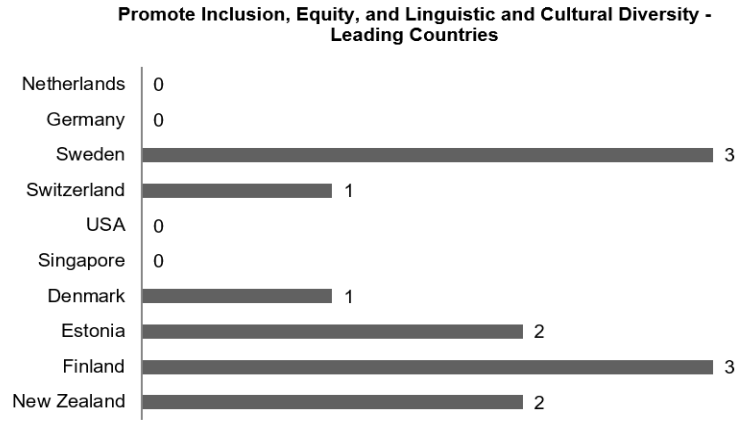


Figure 3

Country Rates of the First Element



The second element, protecting human agency, addresses the risks of overreliance on GenAI and its potential to undermine intellectual development and independent thinking. This element is one of the most widely integrated into university policies, appearing in 76.7% (n = 23) of the universities and 90.0% (n = 9) of the countries, mostly via making learners aware of GenAI's use of their data and protecting learners' intrinsic motivation for self-development. For example, UCPH underscores data protection concerns in its GenAI guideline for students, stating: "The data entered on e.g., ChatGPT 3.5, is not treated confidentially and may be shared with third parties. It is your personal responsibility to only enter information that has either been published or is allowed to be published" (IT University of Copenhagen, 2024, p. 2). Promoting social interaction while preventing overreliance, utilizing GenAI to minimise homework and exam pressure, and consulting stakeholders on GenAI, while important, are less widely represented across the sample. However, they are not entirely neglected, as some universities do reference them in their policies. Tallinn University emphasises social interactions in its Recommendations for the Use of Artificial Intelligence, encouraging students and teaching staff to share their experiences and experiment collaboratively to explore how GenAI can enhance problem-solving

(Tallinn University, 2025). KTH (2024a) recommends using GenAI tools, for example, for notetaking, which would help students with dyslexia or concentration difficulties which not only warn students of the possible dangers of GenAI but also guide them on where and how to use it for their benefit. Some universities invite stakeholders to gather feedback on GenAI. While DTU (2024) involves the student organisation, Polyteknisk Forening in the work of their GenAI guideline, KTH (2024b) hosts the webinar Lunch 'n' Learn for teachers and researchers to share their AI experiences. The adoption of the seven indicators (Table 1) of the element ranged between 26.7% (n = 8) and 56.7% (n = 17) for the universities and between 40.0% (n = 4) and 90.0% (n = 9) for the countries (Fig. 4), showing notable levels of adoption across both groups. The analysis identifies Sweden, Switzerland, Denmark, Finland, and New Zealand as leading nations in this area (Fig. 5), with all selected universities implementing at least one indicator of the element. While there is no clear global pattern in these findings, Nordic countries (i.e. Sweden, Denmark, Finland) show a slight strength in prioritising this element.

Figure 4

Adoption of the Second Element

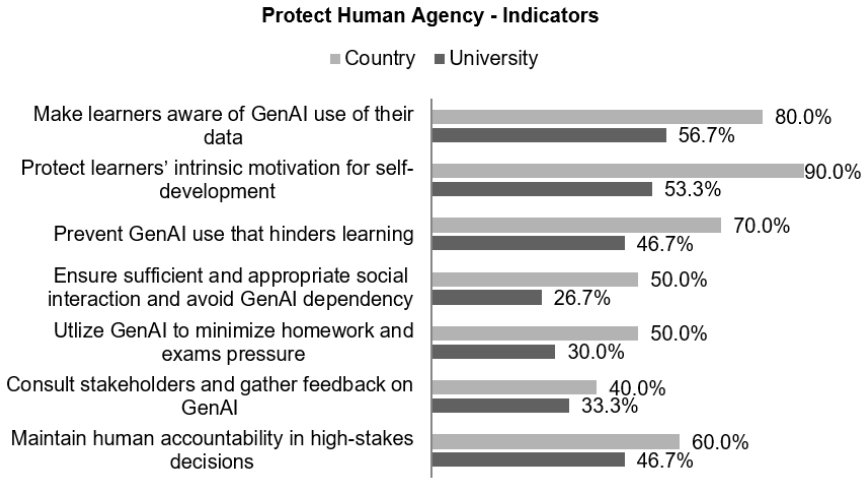
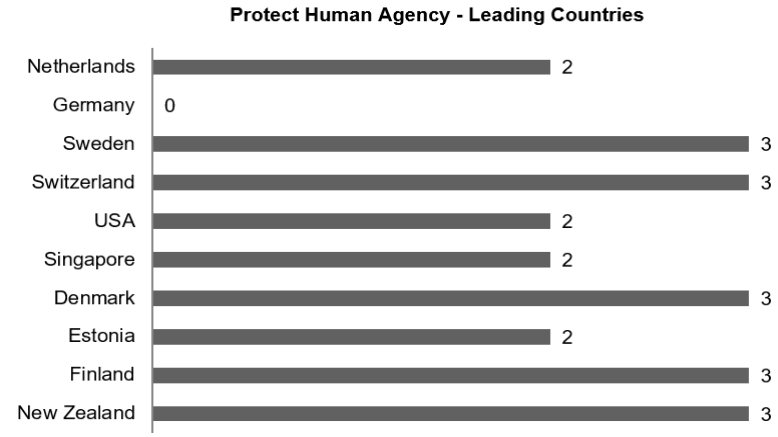


Figure 5

Country Rates of the Second Element



Monitoring and validating GenAI systems underscores the importance of continuous oversight and validation throughout the lifecycle of these systems. It ensures the assessment of ethical risks, pedagogical appropriateness, academic rigour, and the overall impact on students, teachers, and classroom dynamics. It is the second most prominent element in the policies of the selected universities, present in 83.3% (*n* = 25) of the universities and 90.0% (*n* = 9) of the countries. The adoption of the five indicators (Table 1) ranged between 33.3% (*n* = 10) and 73.3% (*n* = 22) for the universities and between 60.0% (*n* = 6) and 90.0% (*n* = 9) for the countries (Fig. 6), reflecting a varied distribution of adoption across both groups, with the highest adoption rates appearing in cases where an ethics-by-design approach is most emphasised. The Netherlands, Sweden, Switzerland, Singapore, Denmark, Finland, and New Zealand are the leading countries (Fig. 7), and each includes at least one of the indicators. There are universities that cover all indicators of the element, too. As an illustration, the University of Tartu (2023), in its guidelines, addresses all indicators of the element by warning that chatbots may not account for cultural differences or social norms, advising that personal data should not be entered without consent, emphasising that outputs must be verified, and stressing that AI use should be guided by purposefulness, ethics, transparency, and critical thinking. While no cohesive global pattern is evident, Nordic countries consistently address monitoring and validating GenAI systems across their universities.

Figure 6

Adoption of the Third Element

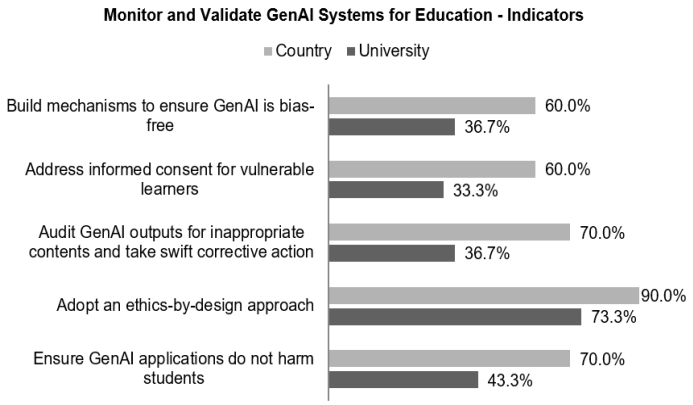
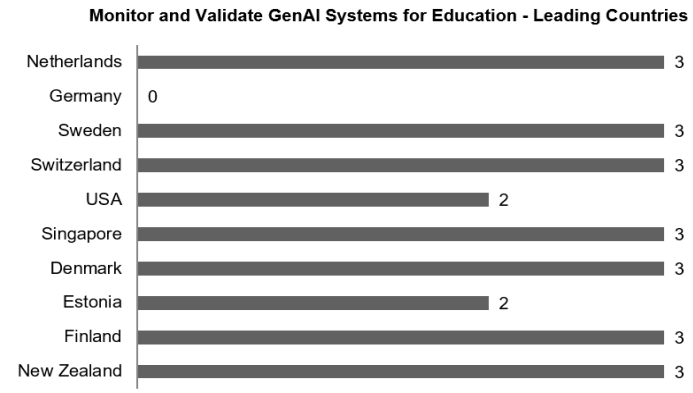


Figure 7

Country Rates of the Third Element



The fourth element, *develop AI competencies*, emphasises equipping learners with the skills necessary for the safe, ethical, and meaningful use of AI, while fostering literacy in both its human and technological dimensions in response to advancements in GenAI. Despite its significance, this principle remains a relatively low priority, addressed by only 43.3% (*n* = 13) of the universities and 60.0% (*n* = 6) of the countries. The adoption of the five indicators (Table 1) ranged between 0.0% (*n* = 0) and 33.3% (*n* = 10) for the universities (Fig. 8) and between 0.0% (*n* = 0) and 50.0% (*n* = 5) for the countries (Fig. 8), reflecting a lower overall adoption compared to previous elements. Notably, the highest adoption rate is seen in the development of AI curricula for different educational levels and fostering creative use. The University of Otago (2024), for example, recommends that their teachers incorporate GenAI tools in teaching and assessment when possible and provide written guidance for students on acceptable use of it. Promoting gender equality and providing special programmes for older workers' reskilling remain absent across both groups. The fact that some universities believe students need to improve their AI skills and that this should be considered when developing courses (Massey University Te Kunenga ki Pūrehuroa, 2023) suggests that the focus is on training newcomers to acquire skills, rather than adapting older employees. Sweden and New Zealand are the leading countries for the element (Fig. 9), as all selected universities implement it.

Figure 8

Adoption for the Fourth Element

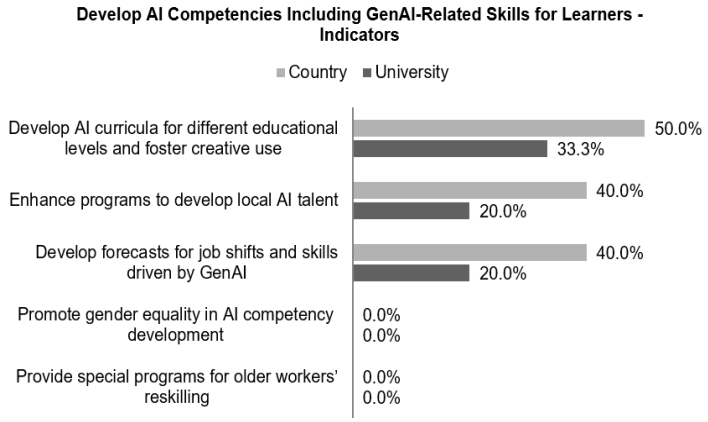
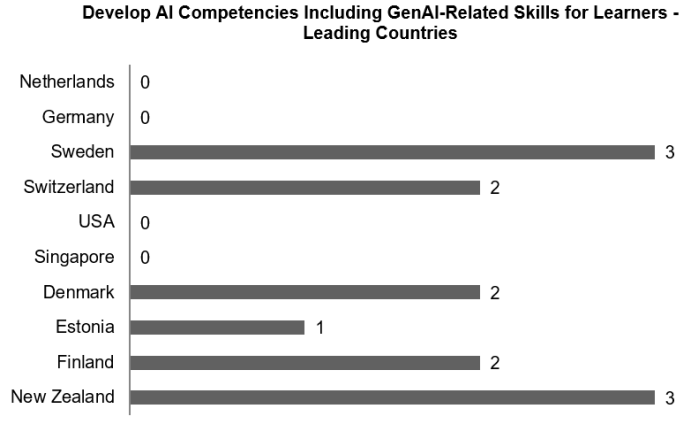


Figure 9

Country Rates of the Fourth Element



The fifth element, *build capacity for educators,* is essential for ensuring that educators are not only competent in using GenAI tools but are also protected and supported in doing so. According to the analysis, 70.0% (*n* = 21) of the universities and 90.0% (*n* = 9) of the countries cover at least one of the indicators (Table 1). The adoption levels respectively are 43.0% (*n* = 13), 57.0% (*n* = 17), 43.0% (*n* = 13), and 33.0% (*n* = 10) for universities and 60.0% (*n* = 6), 90.0% (*n* = 9), 60.0% (*n* = 6) and 50.0% (*n* = 5) for countries (Fig. 10), demonstrating some level of compliance, making this one of the more emphasised areas of the framework (Fig. 1). While Nordic countries, Tallinn in Estonia, and Massey University in New Zealand exhibit commitment, the Netherlands, the USA, and Singapore significantly lag behind (Fig. 11). For example, Aarhus University encourages teachers to experiment with GenAI, integrate it into their teaching, be a role model to their students and discuss the limitations and ethical implications with them (Elving, 2025). The university provides AI courses for teachers at the Centre of Educational Development (Noordeloos, 2024), and tips and advice can be found on AU Studypedia (Jakobsen, 2024a) and AU Educate webpages (Jakobsen, 2024b). On the other hand, Harvard University recommends a brief experimentation, feeding representative assignments into GenAI (n.d.), which only covers one indicator of the element. The findings suggest that although many institutions have begun implementing educator capacity policies, systematic and comprehensive efforts remain insufficient across most regions.

Figure 10

Adoption of the Fifth Element

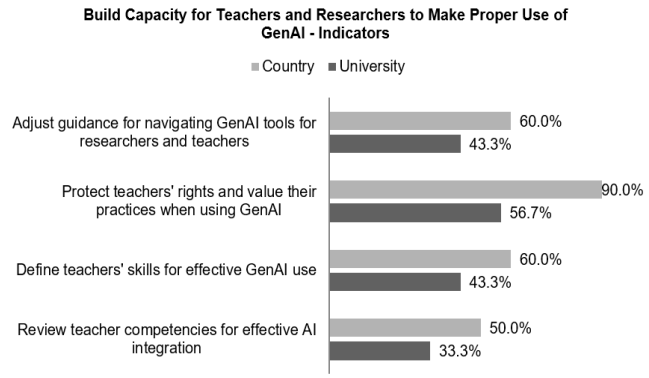
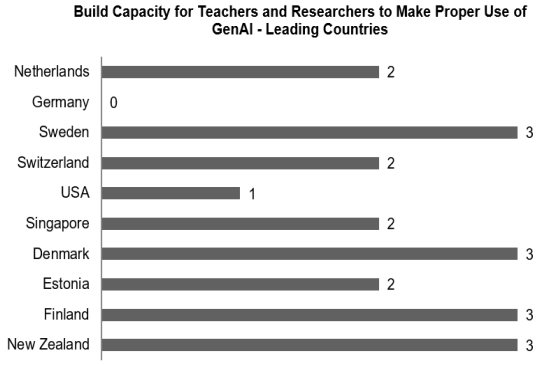


Figure 11

Country Rates of the Fifth Element



The sixth element, *promote plural opinions and plural expressions of ideas,* emphasises critical engagement with GenAI tools, highlighting that learners and researchers should not treat AI outputs as absolute but rather as contestable, experimentable, and open to critique. Based on the analysis, this principle was adopted by 76.7% (*n* = 23) of universities and 90.0% of countries (*n* = 9). The three indicators (Table 1) were adopted by 40.0% (*n* = 12), 63.3% (*n* = 19) and 63.3% (*n* = 19) of the universities, and 50.0% (*n* = 5), 90.0% (*n* = 9) and 90.0% (*n* = 9) for countries, respectively (Fig. 12). Overall, Nordic countries and Estonia exhibit consistent engagement with this principle (Fig. 13), and the USA and Switzerland present fragmented compliance. These results point to a critical gap in promoting reflective and pluralistic AI literacy, especially in institutions focused more on functionality than critical pedagogy. Whereas the University of Tartu (2023) cautions against bias, errors and fictitious sources in GenAI outputs and recommends both experimentation and verification, Stanford University does not address the potential for unreliable information generated by GenAI.

Figure 12

Adoption of the Sixth Element

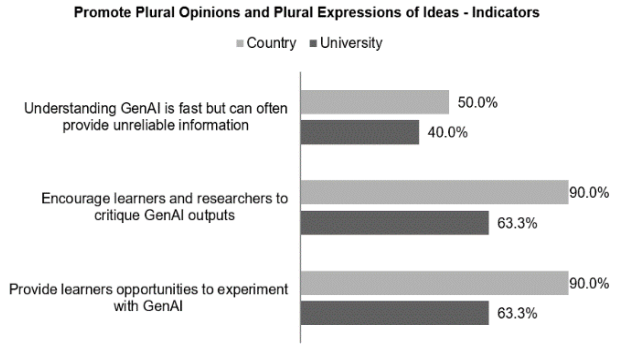
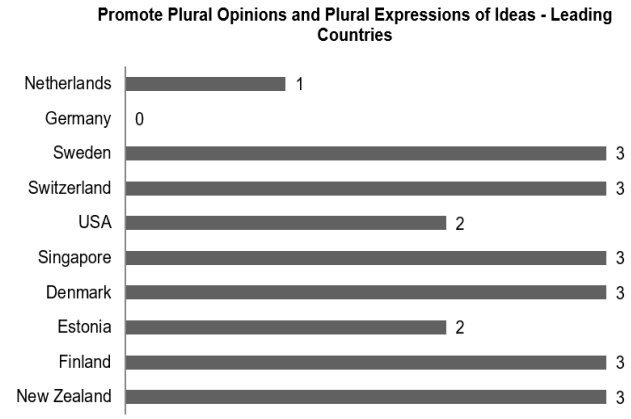


Figure 13

Country Rates of the Sixth Element



The seventh element, *test locally relevant application models and build a cumulative evidence base,* stresses the importance of contextualising GenAI policies through local adaptation, ethical foresight, and innovation. However, it remains inconsistently implemented across institutions and “incentivise GenAI designers for diverse learning” is absent from all policies included in the

study, which indicates a missed opportunity to shape GenAI tools around varied learning needs and socio-cultural diversity. According to the analysis, only 86.7% (*n* = 26) of universities and 90.0% of countries (*n* = 9) address at least one indicator of this component. The adoption rates for eight indicators (Table 1) ranged between 0.0% (*n* = 0) and 60.0% (*n* = 18) for universities and 0.0% (*n* = 0) and 70.0% (*n* = 7) for countries (Fig. 14). Finland stands out as the most comprehensive in aligning with this principle, addressing ethical, strategic, and sustainability dimensions. The University of Helsinki offers AI guidelines in teaching that inform users of the extent of AI use in their courses (n.d.-a), and these guidelines are updated as necessary and as experience with AI grows (n.d.-b). The university also supports the use of GenAI in almost any level of research while warning about the ethics of AI and recommending a responsible and critical use where there are no important implications on others and on the environment (n.d.-b). Countries like the Netherlands and Estonia, on the other hand, do not demonstrate any strategic or inclusive approach (Fig. 15). The USA and Switzerland show partial alignment but do not fully address innovation or environmental concerns, suggesting a narrow operational focus rather than a holistic policy vision.

Figure 14

Adoption of the Seventh Element

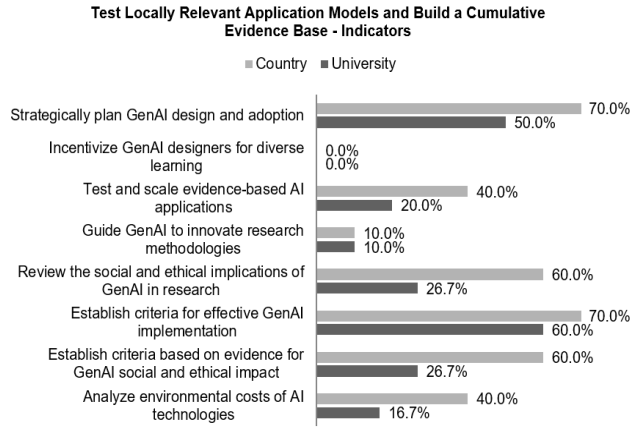
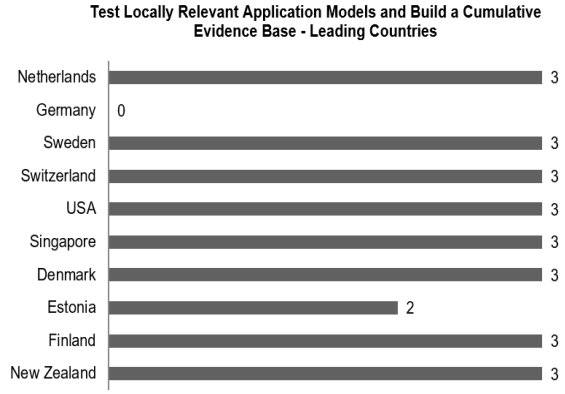


Figure 15

Country Rates of the Seventh Element



The last element, *review long-term implications in an intersectoral and interdisciplinary manner,* emphasises the need for higher education institutions to develop long-term, interdisciplinary strategies for GenAI governance. It calls for multistakeholder collaboration, expert consultation, and regulatory foresight. According to the analysis, this principle is among the least implemented, with only 56.7% of universities (*n* = 17) and 70.0% of countries (*n* = 7) adopting at least one related indicator of the three indicators (Table 1) with adoption rates 33.3% (*n* = 10), 20.0% (*n* = 6), and 30.0% (*n* = 9) for universities, and 70.0% (*n* = 7), 60.0% (*n* = 6) and 50.0% (*n* = 5) for countries, respectively (Fig. 16) Overall, Finland, Sweden, and Denmark emerge as the most consistently implementing multistakeholder engagement -e.g. Lund University discussing the role of GenAI with colleagues (Forsyth, 2024)-, expert consultation -e.g. Uppsala University collaborating on best practices as GenAI evolves (2024)-, and policy feedback mechanisms -e.g. UCPH revising their GenAI guidelines (2024)-, in this dimension (Fig. 17). New Zealand also performs strongly with engagement across all three indicators. In contrast, countries like Switzerland and Estonia, despite their global reputation in digital innovation, show limited engagement. The USA shows isolated best practices at institutions like Harvard and Stanford, but lacks systemic coordination. These results underscore the importance of moving beyond operational GenAI adoption to interdisciplinary and anticipatory policy planning, which remains a significant challenge for many global higher education systems.

Figure 16

Adoption of the Eighth Element

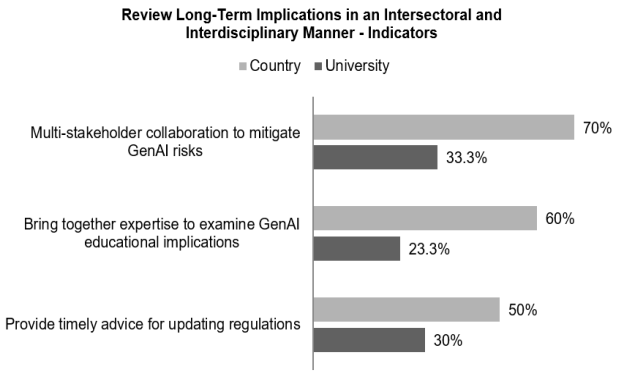
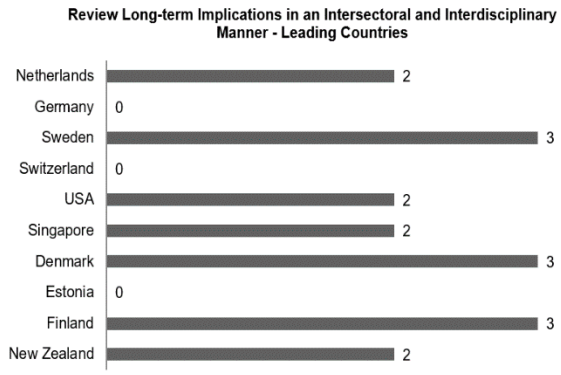


Figure 17

Country Rates of the Eighth Element



Comparison of Country Profiles

Three Nordic countries, and New Zealand, each have at least one university addressing all eight elements, reflecting a holistic approach to GenAI integration by considering not only technical and educational implementation but also ethical, cultural, and long-term governance dimensions. While full element coverage signals balance, total indicator coverage reflects depth and policy intensity. Of 41 indicators, Finland leads with over 30, showing the highest comprehensiveness, especially in sustainability, educator training, and local contextualisation. Sweden follows with approximately 28, placing emphasis on research innovation, pluralism, and ethical safeguards. New Zealand covers over 27, highlighting strengths in educational experimentation, regulatory feedback, and institutional alignment. Denmark addresses 26, showing a robust commitment to capacity building and ethical integration. Estonia covers 22, focusing particularly on agency protection and critical digital literacy. In contrast to Nordic countries and New Zealand, Switzerland, Singapore, and the USA show partial engagement, covering 16-20 indicators, often emphasising technological innovation while demonstrating insufficient focus on participatory governance or environmental concerns. The Netherlands shows engagement across about 15 indicators, with gaps in inclusion, educator policies, and long-term implications. Germany, with no national policy, remains the least compliant, addressing none of the indicators (Table 5).

Discussion

The results of the comprehensive policy analysis revealed that university GenAI policies vary in format, including website publications and formal reports. Most institutions are in the implementation phase, while some remain in the piloting stage. Some universities have multiple GenAI policies, while others do not have any official, publicly available policy. While academic reputation often correlates with policy presence (Xiao et al., 2023; Luo, 2024), the absence of them at leading institutions in Germany and Estonia suggests an exception, which may point to influencing factors beyond institutional prestige. Alternatively, these institutions may rely on informal or unwritten guidance (UNESCO, 2024). Some have recently revised existing AI policies or introduced new ones to incorporate GenAI. While policies are generally at the institutional level, a few universities have adopted national or continental frameworks.

The adoption of GenAI-related principles varies across universities and countries, revealing both strengths and areas that require further attention. Under *promote inclusion, equity, and diversity,* the limited adoption of taking action to promote universal internet connectivity and enhancing human agency suggests that accessibility remains underprioritized. Similarly, within *develop AI competencies,* the absence of efforts to promote gender equality in AI competency development and special programs for older workers' reskilling highlights persistent gaps in inclusivity, which aligns with broader concerns that digital innovation policies often overlook social equity (e.g., Eubanks, 2018; Noble, 2018). GenAI could bridge the complex and persistent educational gaps, yet also increase the digital divide (Capraro et al., 2024). This reinforces the need for a more nuanced approach to GenAI policy development, one that acknowledges not only technological progress but also the persistent disparities in access and inclusivity. Without deliberate efforts to address these gaps, the potential of GenAI to create a more equitable learning environment may remain unrealized. While short-term evaluations of GenAI are essential for accounting for

the real- time evolution of this technology and for developing rapid responses to emerging challenges in higher education, long-term assessment is necessary to ensure its sustainable and ethical use, and there is merit in considering both perspectives (Mishra et al., 2024).

UNESCO's framework encourages institutions to *review long term implications in an intersectoral and interdisciplinary manner;* however, this element remains weakly operationalised in policies. To fill this gap, a future-oriented approach enables universities to examine who benefits and who bears the costs of GenAI, what assumptions and biases are embedded in these systems, how it reshapes academic ecosystems, and how institutions can retain agency in its use (Mishra et al., 2024). In moving forward, school leadership must therefore adopt intentional adoption models that align both the short and long-term implications of GenAI adoption. Additionally, adopting a "learn-it-all and know-it-all" approach (Chiu, 2024), by consulting domain-specific experts, ensures knowledge from multiple disciplines is integrated (Sushereba et al., 2024), supporting a comprehensive implementation that addresses diverse educational domains. Such interdisciplinary integration can also enhance learning experiences and practical skills, preparing students for complex real-world challenges (Xia et al., 2026).

Test local application models also exhibit weaknesses, with little focus on incentivising GenAI designers for diverse learning, guiding GenAI to innovate research methodologies, and analysing the environmental costs of AI technologies, underscoring challenges in fostering sustainable and context-aware AI development. These omissions are concerning, as a one-size-fits-all approach can exacerbate existing inequalities and fail to cater to the varied pedagogical requirements across diverse learners (Lin & Chang, 2024). Furthermore, insufficient guidance for leveraging GenAI in research methodologies represents a missed opportunity, as GenAI can be helpful in research (Rudolph et al., 2024). While AI holds immense potential for data analysis and knowledge discovery, the limited availability of clear frameworks and ethical guidelines for its application in research can lead to methodological biases and reduced transparency. Furthermore, the analysis of the environmental costs associated with AI technologies in educational settings remains largely unaddressed. The energy consumption and carbon footprint of training and deploying large language models are significant (Strubell et al., 2019). This environmental cost and sustainability issue demands a paradigm shift in how AI is developed, deployed, and discarded, urging a move toward more responsible and equitable practices throughout its lifecycle (Rudolph et al., 2024), yet sustainability considerations are often absent from policies surrounding GenAI adoption in higher education.

Conversely, some indicators reflect strong institutional commitments. *Monitor and validate GenAI systems* benefits from a broad uptake of the ethics-by-design approach, reinforcing efforts to embed ethical considerations into AI governance. *Promote plural opinions* sees widespread implementation of opportunities for learners to experiment with GenAI and engage in critical assessment, emphasising the importance of fostering analytical perspectives. Similarly, *test local application models* stand out in its strong adoption of criteria for effective GenAI implementation, ensuring structured and reliable AI integration. However, this element also contains some of the least-adopted indicators, such as incentivising GenAI designers for diverse learning and guiding AI-driven research methodologies, making it a strong example of how adoption rates vary significantly across indicators.

The country-level coverage of GenAI-related elements, determined by whether at least one of its universities adopted a given element, reveals notable disparities across regions. Nordic countries and New Zealand exhibit a comprehensive approach by covering all eight elements. Their policies not only address technological aspects but also emphasise human-centred AI, socio-cultural diversity, and long-term sustainability. Other countries display more selective adoption patterns. Switzerland and Estonia also present strong adoption across nearly all elements, with the exception of element 8, suggesting a relatively lower emphasis on long-term implications. The Netherlands, , and Singapore show engagement with most elements but have limited coverage of elements one and four, potentially indicating a weaker focus on inclusion and AI competency development. Meanwhile, Germany remains outside the coverage due to the absence of a publicly available established policy. This trend contrasts with the findings of Xiao et al. (2023), who emphasise that academic reputation, often linked to rankings such as QS, correlates with the adoption of GenAI policies. However, despite lower rankings in the AIPI, countries like the Nordic nations and New Zealand have exhibited more comprehensive policy adoption than higher-ranked AIPI countries such as the Netherlands and Germany. One possible explanation for this discrepancy is accessibility limitations, as studies by Ullah et al. (2024) and Moorhouse et al. (2023) highlight that many GenAI policies from top universities are not publicly available, suggesting that some policies may exist but remain inaccessible. For those that are accessible, this pattern indicates that, within high AIPI countries, the implementation of GenAI policies is not solely dictated by a country's AIPI ranking. Instead, it likely reflects a combination of local policy priorities, cultural values, and institutional autonomy, which shape the development of more inclusive and sustainable GenAI frameworks.

These findings are similar to Luo (2024) and Dabis and Csáki (2024) about the narrow ethical lens in current policy documents. However, this result also might indicate that countries with advanced AI economies, such as Germany, the USA, and Singapore, do not necessarily show equivalent progress in GenAI education policy frameworks. This divergence suggests that AI policy leadership in research and innovation does not automatically translate into educational foresight or ethical preparedness. The differences also emphasise that adoption is not uniformly distributed across countries and that certain elements receive more attention in specific regions, depending on policy priorities and institutional frameworks. Moreover, this misalignment could stem from the fact that while the UNESCO framework provides a broad and structured approach, its applicability may vary across different national contexts.

Theoretical Implications

Theoretically, the research enriches the growing field of GenAI policy analysis by offering a cross-country comparative lens grounded in a global framework. It validates the applicability of the UNESCO indicators and exposes their operational limitations in institutional settings, thereby inviting further refinement of theoretical models for digital education governance. This study opens several directions for future research. Future studies could build on this study by going deeper into individual elements of the framework. While this analysis identified the presence of indicators and elements, and illustrated how they appear in policies, future studies, for example, could focus on a single element and examine its implications beyond policy documents, by investigating how it is interpreted by stakeholders, how it shapes institutional practices, or what challenges arise in its application. Particular attention could be given to

underrepresented elements. Areas such as inclusion, gender equality, reskilling opportunities for older or non-traditional learners, sustainability, the use of GenAI in research, and consideration of long-term implications remain weakly addressed and focusing on them would help clarify whether the absence reflects low prioritisation or implementation challenges.

Researchers could also apply alternative frameworks, such as those from the OECD (2023) and the UK's Russell Group (2023). Using different frameworks would complement the UNESCO framework by bringing additional aspects of policies into view that may not be explicitly captured within a single analytical lens. This can help identify further dimensions of policies, especially in how they are formulated and translated into practice. Expanding the sample would strengthen comparative insights. Including more universities per country, as well as a wider range of countries would improve the robustness of cross-country comparisons and provide a more comprehensive understanding of policy variation. Finally, future research could incorporate different methodological approaches. Experimental designs, for example, could be used to examine how specific policy components influence teaching, learning, or research practices, offering a more direct assessment of their practical implications.

Practical Implications

The findings of the study highlight areas for improvement in GenAI policy, as reflected in the neglected elements of the UNESCO framework. These gaps provide a clear basis for identifying where and how policies can be strengthened. They thus offer university leadership a clear reference for improving and further developing their policies. The findings underline the need for integrated, future-oriented GenAI policies in higher education. Institutions should prioritise interdisciplinary collaboration, social inclusion, and long-term strategic planning, supported by continuous research and development on GenAI in education (Taylor, 2024). Educational policymakers and university leaders are encouraged to go beyond ethical checklists and engage with evolving technologies through participatory and context-sensitive approaches, supported by multi-stakeholder dialogues that reflect a nuanced understanding of AI's capabilities and limitations (Rudolph et al., 2024).

While universities in high-AIPI countries have broadly addressed GenAI adoption, the research highlights consistent neglect of inclusion and diversity indicators, namely, universal internet connectivity, gender equity in AI competency development, and reskilling for older workers. This is notable given that educational technologies are often assumed to democratise access to education and lifelong learning (Capano et al., 2025). Higher education leaders and policymakers should, therefore, systematically broaden GenAI strategies beyond student-focused digital skills to include underrepresented groups and lifelong learners. This could include targeted digital inclusion initiatives such as funded access to devices and connectivity for disadvantaged learners and institutional partnerships with public and private providers to expand access to reliable internet connectivity and digital infrastructure. Universities could also integrate gender-responsive AI competency programmes, for example, through mandatory institutional requirements to audit GenAI tools for gender bias and ensure that AI systems do not reproduce or amplify such biases. In addition, programmes can be designed specifically for non-traditional and older learners to support continuous upskilling, for example, through short,

flexible GenAI literacy courses offered within the university's continuing education that can be taken alongside work and integrated into staff development.

Similarly, within the UNESCO policy element, Testing Local Application Models, some indicators are being implemented but remain under-addressed - such as incentivising GenAI designers to prioritise diverse learning needs, guiding GenAI use in research, and analysing the environmental impacts. Although implementation is evident, addressing the gaps remains crucial for achieving a more balanced and coherent regulatory approach to GenAI in higher education institutions (Jin et al., 2025). The limited attention suggests a disconnect between university GenAI ecosystems and pedagogical and sustainability imperatives. Universities could establish clear guidelines for the use of GenAI in research, including requirements for transparency in analysis and reporting, and offer short training sessions on appropriate applications in research. To address environmental impact, universities could build on practices in some institutions in the sample (e.g. UCPH explicitly recommends the use of Copilot) by standardising the use of institutionally licensed GenAI tools and reducing reliance on multiple external systems. This could be complemented by providing clear guidance on avoiding unnecessary or repetitive use in teaching and research.

For higher education leaders, future GenAI strategies should include robust institutional incentives for interdisciplinary experimentation, ethical auditing of AI research tools, and integration of environmental impact assessments into digital infrastructure planning (UNESCO, 2023b). Aligning local experimentation with broader societal goals can enhance both the relevance and responsibility of AI-driven educational reforms.

Differences in governance models and institutional priorities suggest that a one-size-fits-all standard may not fully capture the complexities and variations of local implementation, raising questions about the effectiveness of a global framework in diverse educational and policy landscapes. While UNESCO's indicators provide structure, their limited operationalisation highlights the importance of contextual flexibility and institutional autonomy in shaping inclusive and sustainable GenAI frameworks.

Limitations and Future Research

This study focused on the top three universities in the top ten most AI-prepared countries (Zhu, 2024), limiting the generalizability of the findings. Also, the top three universities from each country that emerged based on the analytical criteria may not necessarily be the most progressive or well-informed about GenAI. Noticeably, the set criteria meant that a majority of the universities included in the analysis were from Western contexts, except those from Singapore. The Western and Eurocentric view of GenAI policies brings specificity and contextualisation, which is commendable and deeply informs policy within the regions, but does not provide a universal discourse. Non-Western countries are encouraged to increase their readiness and preparedness to embrace novel technologies like GenAI. At the same time, non-Western international actors or scholars can design or integrate new frameworks or conduct similar research that challenge the dominant Western discourse on digital technology policies.

Additionally, reliance on publicly available documents may overlook internal or evolving policies, while language barriers and limited institutional transparency further constrain access. As Driessens and Pischetola (2024) noted, policies at institutions such as the University of Copenhagen and TU Denmark remain restricted to internal portals, underscoring accessibility. Policy gaps may result from absent national GenAI strategies, legal or ethical uncertainty, or a narrow compliance focus. Fragmentation from institute-level rather than university-wide policies creates inconsistencies. Other barriers include uneven digital readiness, reactive policy-making, and weak alignment with national ethical frameworks, warranting further investigation.

Future research should track policy evolution through longitudinal and ethnographic perspectives, expand to lower-ranked, vocational, or non-Western institutions, and employ mixed methods to explore policy drivers and barriers. Studies can replicate this research by focusing on university operations, assessment, teaching, learning, research, academic performance. Additionally, UNESCO-based quantitative indicators could support benchmarking and impact studies. Researchers should examine how GenAI policies shape pedagogy, academic integrity, and institutional culture, as well as the impact of decentralized policy-making on coherence and effectiveness.

Conclusion

This study explored how leading universities in the top ten AI-prepared countries have developed and implemented GenAI policies aligned with UNESCO's framework. Analysing the policies, it evaluated how eight core elements of responsible GenAI use in higher education were addressed, highlighting policy diversity, commonalities, and gaps across countries. Among the 30 universities examined, 26 had publicly available policies in various formats, while policies from all three German universities and Tallinn University of Technology were not publicly available. The adoption of the UNESCO framework’s elements and indicators differs across universities and countries, which may stem from cultural contexts or moral foundations and social and political dynamics such as national/institutional governance or priorities and local education policies. While the variations are necessary for a context-specific approach to GenAI implementation, it is crucial that institutions do not neglect key elements or ethical concerns that do not promote a safe and responsible use. For example, the seventh element, '*test local application models*,' and the third element, '*monitor and validate GenAI systems*,' are addressed by most policies. In contrast, the first element, '*promote inclusion, equity, and diversity*,' and the fourth element, '*develop AI competencies* and the last element, *“review long-term implications in an intersectoral and interdisciplinary manner"* are the least frequently covered. The policies tend to underprioritize key areas, such as accessibility, gender equality, reskilling of older workers, diversity, the use of GenAI in research, environmental costs and long-term implications. The Nordic countries and New Zealand cover all eight elements and have the most comprehensive approach to GenAI adoption, indicating that policy strength is not directly correlated with the AIPI list.

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