Journal of

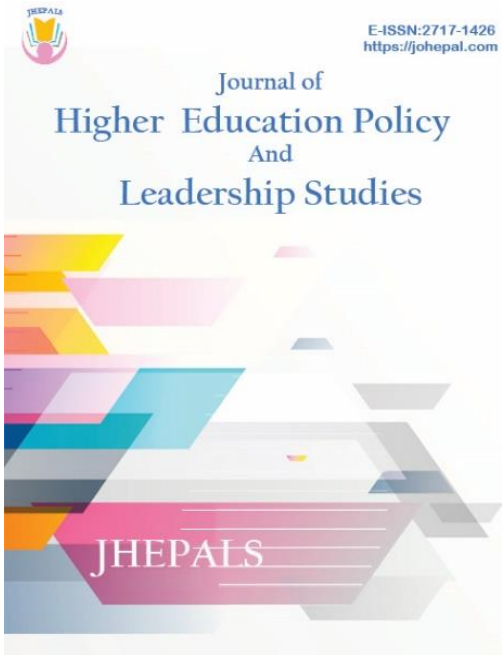
Higher Education Policy

And

Leadership Studies

JHEPALS (E-ISSN: 2717-1426)

https://johepal.com



Governing Generative AI in Higher Education: Policy Archetypes, Cross-Regional Patterns, and an Adaptive Governance Framework

Akram Hosseini
Department of Architecture,
Faculty of Architecture and Urbanism,
Ferdowsi University of Mashhad, Mashhad, IRAN
Email: akram.hosseini@um.ac.ir
https://orcid.org/0000-0001-8080-6925

Elahe Khademzadeh
Faculty of Architecture, Berlin University of Applied Sciences (BHT), Berlin, GERMANY
Email: elkh3257@bht-berlin.de
https://orcid.org/0009-0003-1252-758X

Article Received	Article Accepted	Published Online
2026/05/24	**2026/09/13**	**2026/09/30**

Cite article as:

Hosseini, A., & Khademzadeh, E. (2026). Governing generative AI in higher education: Policy archetypes, cross-regional patterns, and an adaptive governance framework. *Journal of Higher Education Policy and Leadership Studies*, *7*(3), 28-50. https://dx.doi.org/10.66224/johepal.7.3.28

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

Governing Generative AI in Higher Education: Policy Archetypes, Cross-Regional Patterns, and an Adaptive Governance Framework

Journal of Higher Education Policy And Leadership Studies (JHEPALS)

E-ISSN: 2717-1426
Volume: 7 Issue: 3
pp. 28-50
DOI:
10.66224/johepal.7.3.28

Akram Hosseini *
Elahe Khademzadeh

Abstract

The emergence of Generative Artificial Intelligence is reshaping debates and practices surrounding higher education governance and compelling universities to develop policy responses. This study compares GenAI policies across 29 universities in North America, Europe, East and Southeast Asia, Oceania, and institutions in the Middle East, Africa, and Latin America. It examines four questions: which policy archetypes have emerged across major regions; what emerging or hybrid approaches appear beyond these archetypes; what governance principles underpin policy approaches; and how these findings can inform a governance framework for higher education institutions. Using qualitative content analysis with a hybrid inductive–deductive approach, the study identifies four dominant archetypes: Risk-Management and Compliance, Ethical-Framework and Rights-Based, Dialogic and Flexible, and Empowerment and Literacy-First. Emerging approaches are identified in China/East Asia, the Middle East, Africa, and Latin America, while hybrid approaches are observed in North America, reflecting variation in regulatory contexts, institutional resources, and educational practices. Across the sampled universities, three recurrent governance principles emerge: Mandatory Transparency, Ultimate Human Accountability, and Preservation and Cultivation of Critical Thinking. The study synthesizes these findings into a Tripartite Adaptive Governance Framework spanning strategic, operational, and cultural levels, offering a flexible basis for responsible, equitable, and pedagogically sound GenAI adoption.

Keywords: Generative AI; Higher Education Policy; Academic Integrity; AI Governance; Comparative Policy Analysis; Adaptive Governance

* **Corresponding author's email:** akram.hosseini@um.ac.ir

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

Introduction

The public release of advanced Generative AI (GenAI) tools has rapidly reshaped debates and institutional practices surrounding teaching, assessment, research, and academic integrity in higher education (Dwivedi et al., 2023). Institutions have had to move from speculative debate to policy formulation within a relatively short timeframe. Initial reactions ranged from outright prohibition to cautious encouragement, but a clear trend is now visible: a move towards more structured, principle-based governance frameworks that seek to balance the immense pedagogical and research opportunities of GenAI with significant ethical and practical risks (Eaton, 2023).

While a substantial body of literature examines the theoretical implications, ethical dilemmas, and potential applications of GenAI in academia, systematic comparative research on the institutional GenAI policies and guidance that universities are developing remains limited. Recent studies have begun to map national and institutional responses (Parker et al., 2025; Li et al., 2026), yet a fine-grained, cross-regional comparison of institutional policy archetypes remains limited. How are leading higher education institutions (HEIs) translating abstract principles into concrete rules? What governance models are crystallizing, and how do they vary across different regulatory and cultural contexts? Understanding this evolving policy landscape is essential for any institution seeking to develop its own effective and responsible approach.

This study addresses this gap by conducting a qualitative content analysis of publicly available institutional GenAI policies and guidance from 29 leading universities. The sample spans North America, Europe, East and Southeast Asia, and Oceania, and also includes institutions from the Middle East, Africa, and Latin America to capture a broader range of regulatory and cultural contexts. The study aims to identify and compare distinct GenAI policy archetypes across the selected universities and to examine emerging or hybrid approaches in regions where these dominant archetypes do not fully capture the observed policy approaches. It further seeks to identify common governance principles across the sampled policies and synthesize the findings into a flexible, context-sensitive governance framework for higher education institutions.

The significance of this research is both scholarly and practical. Theoretically, it contributes to the literature on technology governance in higher education by identifying empirically grounded policy archetypes across the selected regions and examining common governance principles that cut across these approaches. Practically, it offers educators, administrators, and policymakers an empirically informed conceptual framework derived from the policies of selected institutions. By moving beyond individual institutional case studies, this analysis provides a comparative reference for higher education institutions examining GenAI policy development.

Literature Review

The integration of Artificial Intelligence (AI), and particularly Generative AI (GenAI), into higher education is a rapidly evolving, multi-disciplinary field of scholarly inquiry. This review synthesizes existing literature along four key thematic strands: (1) the disruptive potential and inherent challenges of GenAI for academic ecosystems, (2) the spectrum of proposed theoretical, pedagogical, and ethical responses, (3) the emerging empirical literature on

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

institutional reactions and comparative policy analysis, and (4) the specific gap this study addresses: the need for a fine-grained, cross-regional typology of institutional policy archetypes.

Opportunities and Profound Challenges

A growing body of literature suggests that GenAI represents not merely an incremental change but a transformative force with the potential to reshape the core functions of higher education. Scholars highlight AI's potential as a powerful pedagogical tool for personalized and adaptive learning, with recent advances in GenAI expanding these possibilities through real-time feedback and tailored student support (Popenici & Kerr, 2017; Zawacki-Richter et al., 2019; Kasneci et al., 2023). It promises efficiency gains by automating administrative and instructional tasks such as generating lesson plans, quiz questions, or providing initial feedback on drafts, freeing educator time for higher-order interactions. Furthermore, it can significantly augment research processes through advanced literature synthesis, data analysis, hypothesis generation, and even drafting (Dwivedi et al., 2023). It is seen as a catalyst for creativity, acting as a brainstorming partner, and a potential democratizer of educational support.

Concurrently, a substantial and growing body of literature details profound, systemic challenges. Foremost is the substantial challenge to traditional models of academic integrity and assessment. The ease of generating coherent, seemingly original text has escalated concerns about plagiarism and contract cheating to a new level, complicating or even nullifying traditional take-home assignments and unsupervised assessments (Wang et al., 2024; Cotton et al., 2023). This is intrinsically linked to the risk of cognitive offloading or "digital laziness," where over-reliance on AI may erode students' foundational critical thinking, problem-solving, deep reading, and knowledge synthesis skills—the very skills higher education aims to cultivate (Sullivan et al., 2023). Beyond integrity, significant ethical concerns are paramount. Data privacy and security risks arise when sensitive institutional, research, or personal student data is input into public, proprietary AI platforms with opaque data usage policies. Algorithmic bias and fairness are major issues, as GenAI models often perpetuate and amplify societal biases present in their training data, potentially leading to unfair or discriminatory outcomes in educational contexts (UNESCO, 2023). Authorship, intellectual property, and copyright become murky when AI is involved in content creation, challenging traditional notions of originality and ownership. Unequal access to AI technologies and differences in the digital capabilities required to use them effectively may further reproduce or deepen existing educational inequalities (Williamson & Eynon, 2020).

Navigating the Disruption

In response to these challenges, the literature proposes a range of normative frameworks and strategic responses. A recurring theme in the literature is the call for a fundamental shift from a detection and punishment paradigm towards a prevention, education, and redesign paradigm (Eaton, 2023). This involves moving beyond a reliance on (often flawed) AI-text detectors and instead rethinking assessment design to make it more "AI-resistant" or, preferably, "AI-embracing." This includes focusing on process over product, incorporating reflective components, oral defenses (viva voce), in-class activities, collaborative projects, and assessments tied to personal experience or current local events (Cotton et al., 2023). At

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

the ethical level, proposed guidelines frequently converge on a set of core principles. Transparency and accountability are frequently identified as foundational principles in the broader AI ethics literature (Jobin et al., 2019). The principle of pedagogical purpose dictates that AI use should demonstrably enhance specific learning outcomes rather than merely serve as a shortcut. Scholars increasingly advocate for AI literacy as a critical component of modern education, necessary to empower both students and faculty to use AI systems not just technically, but critically, ethically, and effectively (Long & Magerko, 2020). This literacy encompasses understanding how these tools work, their limitations, their ethical implications, and strategies for critical evaluation of their outputs.

The Emerging Empirical Literature on Institutional Responses

A nascent but rapidly growing strand of literature has begun to document and analyze institutional and national responses to GenAI. Early studies provided valuable snapshots of the initial chaos, describing the range of immediate reactions from outright bans to cautious encouragement (e.g., Sullivan et al., 2023). More recent work has moved beyond single-institution case studies toward systematic, comparative analysis. For instance, Parker et al. (2025) conducted a comparative analysis of AI policies across 343 leading universities in five countries, identifying significant regional differences in policy focus and the degree of instructor autonomy. Similarly, Li et al. (2026) proposed a structured framework (UPDF-GAI) for developing university policies on GenAI governance, based on a cross-national comparison of institutions in the United States, Japan, and China. At the institutional level, An et al. (2025) analyzed GenAI guidelines from 50 leading U.S. universities and identified four core themes: the integration of GenAI in learning and assessment, its use in visual and multimodal media, security and ethical considerations, and academic integrity. Their findings also highlight the need for flexible, stakeholder-specific institutional guidance. Collectively, these studies map important dimensions of institutional GenAI responses but remain limited in geographical scope or analytical focus and have not fully developed a fine-grained, cross-regional typology of institutional policy archetypes.

Existing literature also points to several recurring orientations in institutional GenAI governance, including risk control and compliance, rights- and ethics-based governance, participatory and flexible approaches, and capacity-building through AI literacy and empowerment. However, these orientations have largely been discussed as individual principles or strategic responses rather than synthesized into empirically derived policy archetypes across diverse institutional and regional contexts.

The Specific Gap

Building on this literature, the specific gap lies in the absence of a fine-grained, empirically grounded typology of institutional GenAI policy archetypes derived from systematic comparison of formal university documents across diverse regions. Such an analysis can show how universities translate abstract ethical and strategic principles into concrete rules, how different governance models emerge, and how these approaches vary across geopolitical, cultural, and regulatory contexts. Institutional policies are particularly important in this regard because they provide the formal mechanisms through which governance principles are operationalized: they shape behavior, allocate resources, define permissible practices, and establish institutional norms.

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

This study addresses this gap by systematically comparing the policies of selected universities across diverse regions to identify emergent governance archetypes and common principles. The resulting empirical mapping provides the basis for a flexible, context-sensitive framework to inform GenAI policy development beyond the sampled cases.

Research Methodology

This study employed an exploratory qualitative comparative research design to examine how selected universities have formally approached the governance of Generative AI (GenAI). The study addressed four research questions concerning the identification of policy archetypes, emerging or hybrid approaches, common principles across the sampled institutions, and the synthesis of these findings into a flexible governance framework. Given the limited availability of established categories for comparing university GenAI policies, the analysis followed a hybrid inductive–deductive approach, in which themes were first identified from the policy documents and subsequently organized into broader analytical categories (Fereday & Muir-Cochrane, 2006).

The unit of comparison was the university, while official institutional policy documents constituted the primary data sources. Documents were included when they addressed the use of GenAI in teaching, learning, assessment, or research and were issued or formally endorsed by an authoritative university body, such as a central administration, senate, provost's office, teaching and learning centre, academic integrity office, or IT unit. Where no university-wide policy was available, officially adopted faculty- or department-level guidance was included as supplementary evidence.

A purposive maximum-variation sampling strategy was used to select 29 universities (Patton, 2015; Yin, 2018). The sample was constructed to provide variation across North America, Europe, East and Southeast Asia, Oceania, the Middle East, Africa, and Latin America, as well as variation in institutional policy orientations. The aim was analytical comparison rather than statistical representation. The selected universities included prominent institutions such as Harvard, MIT, Stanford, Oxford, Cambridge, ETH Zurich, Utrecht, the University of Tokyo, the National University of Singapore, Yonsei University, the Australian National University, and the University of Melbourne, together with selected institutions from the Middle East, Africa, and Latin America.

Data were collected between January and December 2025 from publicly accessible official university sources. These included central university policy pages and announcements, teaching and learning centres, academic integrity offices, IT and information-security units, and relevant faculty or student guidance pages. Search terms included *generative AI policy*, *ChatGPT guidelines*, *AI in education acceptable use*, and *academic integrity artificial intelligence*. Retrieved documents were archived and catalogued by university, document type, date, and issuing unit.

Data analysis was conducted using NVivo 14 and proceeded iteratively. First, documents were reviewed to identify their scope, emphasis, and policy orientation. Second, inductive open coding was applied to provisions concerning permissions, restrictions, principles, responsibilities, rationales, and implementation mechanisms (Charmaz, 2015). Third, related codes were consolidated into a codebook of 12 thematic categories, including

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

Data Security and Privacy, Assessment Redesign, Equity and Access, and Governance Structure. Fourth, the codebook was applied across the 29 university cases to develop comparative policy profiles. Archetypes were assigned based on the dominant governance orientation reflected in the combination of themes, policy mechanisms, and stated rationales within each university case. Cases without a sufficiently dominant orientation were classified as hybrid, while substantively distinct configurations not fitting the four dominant archetypes were classified as emerging.

To identify principles shared across the sampled institutions, theme frequencies were calculated at the university-case level. A threshold of 72% (21 of 29 cases) was used as a screening criterion for highly prevalent themes. Frequency counts were interpreted descriptively and were not treated as evidence of statistical generalizability. Themes meeting the threshold were subsequently examined qualitatively to assess their conceptual coherence and relevance as governance principles. This process resulted in the identification of three recurrent governance principles across the sample: Mandatory Transparency, Ultimate Human Accountability, and Preservation and cultivation of Critical Thinking.

The final stage synthesized the identified archetypes and principles into the proposed Tripartite Adaptive Governance Framework, organized across strategic, operational, and cultural levels. The framework was developed by relating the empirical findings to relevant governance principles/literature.

Several procedures were used to strengthen the trustworthiness of the analysis, including comparison of multiple documents within institutions, peer debriefing, direct use of documentary evidence, and reflexive documentation of analytical decisions. Two independent coders separately coded six university cases (approximately 20% of the sample). Initial agreement was 84%, and Cohen's kappa was $\kappa = 0.79$, indicating substantial agreement. Coding discrepancies were subsequently discussed and resolved before the final analysis.

The study has several limitations. The sample is purposive and relatively small, and therefore the findings are not statistically generalizable to universities as a whole. The analysis focuses on formal policy documents rather than policy implementation in practice and may overrepresent prominent institutions with publicly accessible policies. In addition, the study reflects a policy landscape that was evolving rapidly during 2025 and is limited primarily to English-language documents and official English translations. The four archetypes should therefore be understood as dominant patterns within the sampled cases rather than exhaustive categories of university GenAI governance. Similarly, the three principles identified represent recurring patterns across the sample rather than universal principles applicable to all higher education institutions.

Findings

The comparative analysis of GenAI policies from 29 universities revealed a complex and evolving landscape. Distinct policy orientations emerged within the sample, with substantial convergence around several governance concerns. The findings are organized into four interconnected dimensions: (1) four dominant policy archetypes, (2) emerging and hybrid models, (3) common governance principles across the sampled universities, and (4) selected implementation frameworks and tools.

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

Dominant Policy Archetypes: Four Models of Governance

The analysis identified four dominant policy archetypes, each concentrated in particular regional clusters within the sample (see Table 2). These archetypes account for the majority of the institutions analyzed, while several universities displayed hybrid or emerging approaches that did not fit neatly into a single model.

The Risk-Management & Compliance Model (Predominant in North American Cases)

Exemplified by institutions such as Harvard University and the Massachusetts Institute of Technology (MIT), this model is characterized by a procedural and risk-oriented approach. Its primary focus is on institutional risk mitigation, particularly data security, privacy, compliance, and intellectual property (Harvard University Office of the Provost, 2023; MIT Information Systems & Technology, 2025). Institutional guidance places particular emphasis on information-security requirements and the assessment of AI tools before they are used with university data (Harvard University Office of the Provost, 2023; MIT Information Systems & Technology, 2025). Key features include:

Strict Data Prohibitions: Explicit restrictions on entering confidential university data, non-public research data, or sensitive personal information into publicly available GenAI tools. Harvard, for example, prohibits the use of confidential data in publicly available tools unless the relevant tool has been appropriately assessed and approved (Harvard University Office of the Provost, 2023; MIT Information Systems & Technology, 2025).

Pre-Vetting and Centralized Approval: Institutional processes for assessing the security and privacy risks of GenAI tools before they are used with university data, together with the use of approved or institutionally licensed applications (Harvard University Office of the Provost, 2023; MIT Information Systems & Technology, 2025).

Contractual Scrutiny: Attention to the privacy, security, and contractual conditions associated with commercial AI vendors and institutionally procured tools (MIT Information Systems & Technology, 2025; Harvard University Office of the Provost, 2023).

Disclosure and Accountability: Transparency regarding AI use is linked to institutional accountability, while users remain responsible for reviewing and validating AI-generated content before publication or submission (Harvard University Office of the Provost, 2023; Stanford University Information Technology, 2025).

The Ethical-Framework & Rights-Based Model (Predominant in European Cases)

Represented by universities such as the University of Oxford and Utrecht University, this model is characterized by principle-based governance and an explicit emphasis on ethical and rights-related considerations. Relevant policy contexts include the EU's GDPR and AI Act (Regulation (EU) 2024/1689), the UK's data protection regime, and Switzerland's Federal Act on Data Protection (FADP). The focus extends beyond risk mitigation to the conditions for ethical and pedagogically appropriate use. Key features include:

Structured Ethical Principles: Policies are built around explicit principles. Oxford's approach centres on transparency, rigour, and respect, alongside accountability and academic integrity (University of Oxford, 2025a). Similarly, ETH Zurich's guidelines emphasize responsibility, transparency, and fairness (ETH Zurich, 2024).

Promotion of Secure University Platforms: Policies encourage the use of institutionally licensed and appropriately secured platforms for university-related work, particularly where

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

sensitive or confidential data are involved. Oxford provides institutionally supported access to approved AI services for staff and students, alongside guidance on appropriate use with university data (University of Oxford, 2025b; University of Oxford, 2025c).

Tiered and Flexible Integration Frameworks: A notable feature is the use of graduated models of permissible AI use. Utrecht University's five-level scale ranges from no permitted AI use to more extensive and transparent integration, allowing instructors to align AI use with particular learning objectives and assessment requirements (Utrecht University, 2025).

Alignment with Broader Digital Ethics: Policies connect AI use with wider commitments concerning responsible digital practice, human values, and institutional responsibility (ETH Zurich, 2024).

The Dialogic & Flexible Model (Predominant in East and Southeast Asian Cases)

Represented by institutions such as the National University of Singapore (NUS) and the University of Tokyo, this model prioritizes contextual adaptability, instructor autonomy, and dialogue over uniform, top-down rules. The pattern is particularly evident in policies that leave substantial room for course- or department-level interpretation and emphasize communication between instructors and students. Key features include:

Devolution of Decision-Making: Individual instructors, departments, or faculties are given substantial discretion to determine appropriate AI use based on course objectives, disciplinary norms, and pedagogical judgment. The University of Tokyo states that it does not uniformly prohibit generative AI and that decisions regarding use in individual courses are entrusted to the instructor (University of Tokyo, 2023). Similarly, NUS's History Department advises students to communicate with their instructors regarding AI use in their courses (NUS Department of History, 2025).

Conversation over Control: Policies frame AI governance as a shared responsibility involving communication between instructors and students. NUS emphasizes shared responsibility in its interim policy (National University of Singapore, 2025), while departmental guidance encourages discussion of permissible AI use (NUS Department of History, 2025). The University of Tokyo's 2024 survey on generative AI provision also incorporated community input into the development of institutional responses (University of Tokyo, 2024).

Focus on the Learning Process: Policy guidance emphasizes meaningful learning, understanding, and critical engagement rather than task completion alone. The University of Tokyo warns that reliance on AI-generated text can reduce opportunities for students to develop their own thinking processes (University of Tokyo, 2023). The NUS History Department similarly cautions against over-reliance on GenAI because it may reduce opportunities to develop research, analytical, and interpretive skills (NUS Department of History, 2025).

Explicit Skepticism of Detection Tools: Some policies caution against treating AI-detection software as definitive evidence of misconduct. The University of Tokyo, for example, emphasizes dialogue and process-oriented learning rather than relying primarily on technological detection (University of Tokyo, 2023).

The Empowerment & Literacy-First Model (Predominant in Oceania)

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

Digital Equity & Quality in HE

Represented by the Australian National University (ANU) and the University of Melbourne, this model adopts a capacity-building approach centred on preparing students and staff to use GenAI responsibly and effectively. A central emphasis is on building an informed and capable university community (Australian National University, 2024; University of Melbourne, 2025). Key features include:

Mandatory AI Literacy Education: The provision of required or strongly encouraged learning resources and training for students and staff, covering practical use, ethical issues, limitations, and critical evaluation of AI outputs (Australian National University, 2024).

Policy as an Extension of Curriculum: Policy communication and guidance are treated as part of developing a culture of responsible AI use, rather than solely as mechanisms for restricting behaviour (Australian National University, 2024; University of Melbourne, 2025).

Proactive Support for Innovation: Alongside assessment boundaries, these policies provide resources and guidance to help educators experiment with GenAI in teaching and research while maintaining academic and ethical standards (University of Melbourne, 2025).

National Policy Coordination: The Australian cases in the sample also show references to broader national and sector-level guidance on GenAI in higher education, alongside institution-specific policies (Australian National University, 2024; University of Melbourne, 2025).

Table 1.
Overview and Classification of Analyzed Universities by GenAI Policy Archetype

University	Country	Region	Archetype	Key Policy Focus	
1	Harvard University	USA	North America	Risk-Management & Compliance	Confidential data prohibition, AI transparency statements, advisory guidelines
2	Massachusetts Institute of Technology (MIT)	USA	North America	Risk-Management & Compliance	Vendor assessment, data risk levels, compliance with FERPA/HIPAA
3	Stanford University	USA	North America	Risk-Management & Compliance	Data security, responsible use guidelines, AI Playground platform
4	Cornell University	USA	North America	Risk-Management & Compliance	Faculty guides, focus on assessment redesign
5	University of Toronto	Canada	North America	Hybrid (Risk-Management + Pedagogical)	Balance of security and pedagogical innovation, hybrid pattern
6	McGill University	Canada	North America	Hybrid (Risk-Management + Faculty Development)	Workshops, resources for instructors, flexible course-level policies
7	University of British Columbia (UBC)	Canada	North America	Risk-Management & Compliance	Guidelines for instructors, emphasis on teaching and learning support
8	University of Oxford	UK	Europe	Ethical-Framework & Rights-Based	Secure university platforms, no AI in exams unless explicitly permitted, three principles: ethics, accountability, transparency
9	University of Cambridge	UK	Europe	Ethical-Framework & Rights-Based	Principle-driven, UK GDPR-compliant, secure tools
10	University of Edinburgh	UK	Europe	Ethical-Framework & Rights-Based	Ethics & compliance framework, toolkit, literacy focus
11	Utrecht University	Netherlands	Europe	Ethical-Framework & Rights-Based	Tiered Integration Model (5 Levels), scalable use framework, mandatory documentation

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

12	ETH Zurich	Switzerland	Europe	Ethical-Framework & Rights-Based	Three pillars: responsibility, transparency, fairness; human dignity; continuous guideline updates
13	Technical University of Munich (TUM)	Germany	Europe	Ethical-Framework & Rights-Based	Curriculum integration, practical responsible use in degree programs
14	University of Tokyo	Japan	East Asia	Dialogic & Flexible	Decentralized (departmental autonomy), emphasis on meaningful learning, dialogue over detection
15	Yonsei University	South Korea	East Asia	Dialogic & Flexible	"Mutual Agreement" Model, instructor-student consensus, responsible use checklists
16	Seoul National University	South Korea	East Asia	Dialogic & Flexible	Agreement-based model (similar to Yonsei), ethical use emphasis
17	Peking University	China	East Asia	State-Guided Ethical (Emerging)	Regulated flexibility, aligned with institutional guidelines
18	Tsinghua University	China	East Asia	State-Guided Ethical (Emerging)	Structured policy with scope for departmental adaptation
19	Chinese University of Hong Kong (CUHK)	Hong Kong	East Asia	Dialogic & Flexible	Flexible & contextual model, multiple permitted approaches
20	National University of Singapore (NUS)	Singapore	Southeast Asia	Dialogic & Flexible	Dialogue & shared responsibility, transparency declaration, critical analysis of AI output
21	Australian National University (ANU)	Australia	Oceania	Empowerment & Literacy-First	AI literacy curriculum, critical and ethical use, "AI literacy before AI use"
22	University of Melbourne	Australia	Oceania	Empowerment & Literacy-First	Active adoption with formal policies, structured assessment guidelines
23	University of Sydney	Australia	Oceania	Empowerment & Literacy-First	Controlled innovation, training and support services, literacy focus
24	Monash University	Australia	Oceania	Empowerment & Literacy-First	Ethical use framework, staff and student training
25	University of Queensland	Australia	Oceania	Empowerment & Literacy-First	Integration of AI literacy across programs
26	King Saud University	Saudi Arabia	Middle East	State-Guided Ethical (Emerging)	SDAIA six-principle framework (responsibility, privacy, human-centric, equity, transparency, continuous learning)
27	University of Jordan	Jordan	Middle East	State-Guided Ethical (Emerging)	AI as supportive tool (not replacement), legal basis under Jordanian Universities Law, free Gemini access
28	University of Cape Town	South Africa	Africa	Equity-Aware Adaptation (Emerging)	Focus on digital divide, accessible tools, contextual challenges
29	University of São Paulo	Brazil	Latin America	Equity-Aware Adaptation (Emerging)	In early stages of policy formulation, exploring global benchmarks

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

Table 2.
Summary of four dominant regional archetypes in higher education

Archetype	Region	Primary Governance Focus	Typical Mechanisms	Exemplar Institutions
Risk-Management & Compliance	North America (USA, Canada)	Institutional Liability & Legal Duty	Data security, privacy law compliance, risk mitigation; data classification schemes, IT pre-approval processes, vendor contract review, mandatory disclosure as audit trail	MIT, Harvard, Stanford, UBC, Cornell
Ethical-Framework & Rights-Based	Europe (UK, EU, Switzerland)	Human Dignity & Principle-Based Regulation	Ethical integration, data sovereignty, pedagogical alignment; published ethical principles, secure university platforms, tiered use frameworks (e.g., Utrecht 5-Level)	Oxford, Cambridge, ETH Zurich, Utrecht, Edinburgh, TUM
Dialogic & Flexible	Asia (East & Southeast Asia)	Contextual Adaptation & Relational Trust	Instructor autonomy, learning process, community dialogue; department-/instructor-level policy setting, student–instructor conversation, skepticism of detection tools	NUS, University of Tokyo, Yonsei, CUHK, Seoul National University
Empowerment & Literacy-First	Oceania (Australia)	Capacity Building & Systemic Preparation	AI literacy, curriculum integration, innovation support; mandatory AI literacy modules, policy as curriculum extension, national coordination	ANU, Melbourne, Sydney, Monash, Queensland

Emerging and Hybrid Models: Beyond the Four Archetypes

While the four archetypes capture the dominant patterns in the sample, several institutions—particularly in the Middle East, Africa, and Latin America—displayed policy approaches that did not align neatly with a single archetype. These cases indicate additional patterns associated with different regulatory, institutional, and resource contexts that are not fully captured by the four dominant models.

State-Guided Ethical Model (China and Middle East)

Several emerging cases in the sample, particularly Peking University and Tsinghua University in China and King Saud University and the University of Jordan in the Middle East, reflected a stronger alignment between institutional GenAI guidance and broader national or system-level policy frameworks. These cases are grouped as a State-Guided Ethical model because their institutional GenAI governance reflects broader regulatory, ethical, and system-level policy contexts, with institutional guidance shaped by structured governance frameworks beyond individual course-level decisions.

In the Chinese cases, Tsinghua University established a comprehensive, university-wide framework for AI use in education, incorporating principles of human responsibility, compliance and integrity, data security, critical thinking, and fairness (Tsinghua University, 2025). Peking University has likewise developed and supported structured guidance on the boundaries and responsible use of AI in higher education, including principles concerning compliance, equity, and responsible application (Peking University, 2024). These cases therefore illustrate emerging forms of structured and regulated flexibility rather than a uniformly centralized model.

In the Middle Eastern cases, King Saud University's guidelines align with the Saudi Data and AI Authority (SDAIA) six-principle framework, including responsible use, privacy and data security, human-centeredness, fairness and accessibility, transparency and accountability, and continuous learning and feedback, with implementation at the college level (King Saud University, 2025). The University of Jordan frames AI as a supportive tool rather than a

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

replacement, within the context of the Jordanian higher education system and a national initiative providing university students with access to Gemini (University of Jordan, 2025).

Although the institutional contexts differ between China and the Middle East, these cases share an explicit institutional linkage to broader national or system-level AI frameworks and are therefore treated as emerging cases within the State-Guided Ethical category.

Equity-Aware Adaptation Model (Africa and Latin America)

Institutions such as the University of Cape Town (South Africa) and the University of São Paulo (Brazil) displayed a pronounced focus on equity, access, and contextual adaptation. Their policies recognize the potential for unequal access to AI technologies to reinforce existing inequalities and emphasize accessible tools, alternative assessment arrangements, and approaches adapted to local conditions (University of Cape Town, 2025; Universidade de São Paulo, 2025). This pattern places greater emphasis on equitable access and contextual responsiveness than on uniform institutional rules.

Hybrid Models

A small number of institutions—notably the University of Toronto and McGill University in Canada—presented combinations of elements found across multiple archetypes. For example, the University of Toronto combines data-security and privacy requirements with pedagogical guidance, instructor resources, and flexible approaches to course-level GenAI use (University of Toronto, 2025). McGill University similarly combines institutional principles, faculty autonomy, and educational support for responsible GenAI use (McGill University, 2025). These cases illustrate how institutional policies may combine elements of different governance orientations rather than conforming to a single archetype.

Common Governance Principles: Three Recurrent Principles

Despite the diversity of approaches described above, the analysis revealed a strong convergence around three highly prevalent governance principles. Three recurrent governance principles were identified across the sample: Mandatory Transparency (22/29), Ultimate Human Accountability (21/29), and Preservation and Cultivation of Critical Thinking (24/29). Rather than representing a uniform global policy standard, these principles indicate a high degree of convergence within the present comparative sample.

Principle 1: Mandatory Transparency

In 22 of the 29 university cases, students, and in some cases researchers, were required to explicitly disclose the use of GenAI in submitted work (Harvard University Office of the Provost, 2023; University of Oxford, 2025a; National University of Singapore, 2025).In some policies, this is operationalized through "AI Transparency Statements" or declarations specifying the tool used, the nature of the interaction, and the extent to which AI contributed to the work (University of Tokyo, 2023). In many cases, non-disclosure is treated as a form of academic misconduct, sometimes equated with plagiarism (NUS Department of History, 2025). The principle therefore places particular emphasis on transparency regarding AI use.

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

Principle 2: Ultimate Human Accountability

Across the sampled policies, responsibility for AI-assisted outputs remains with the human user, including students, researchers, and faculty (MIT Information Systems & Technology, 2025; ETH Zurich, 2024). This includes verifying factual accuracy, reviewing AI-generated content for errors or bias, ensuring appropriate attribution or citation, and maintaining academic standards (University of Oxford, 2025b; Australian National University, 2024). Human users, rather than AI systems, therefore remain responsible for the quality and ethical standing of their work. (University of Melbourne, 2025).

Principle 3: Preservation and Cultivation of Critical Thinking

The large majority of policies position AI as a supplement to, rather than a replacement for, human cognition and critical engagement. They warn against cognitive offloading, shortcutting, and practices that may undermine the learning process (University of Tokyo, 2023). This principle is reflected particularly in assessment guidance, with policies encouraging or requiring instructors to design tasks that directly assess reflection, synthesis, application of knowledge, argumentation, and oral explanation (University of Melbourne, 2025). The underlying emphasis is on using AI to support learning while preserving students' opportunities to develop and demonstrate independent thinking.

Innovative Implementation Frameworks and Tools

Beyond the archetypes and principles, the analysis identified several operational practices and frameworks across the sampled institutions.

The Utrecht Five-Level AI Index: Utrecht University provides a graduated framework for specifying permissible AI use in assessment, ranging from no permitted use to more extensive and transparent integration (Utrecht University, 2025):

- Level 1: No AI. AI use is not permitted, except for limited functions such as basic grammar or spelling support.
- Level 2: AI as Ideation/Brainstorming Partner. AI may be used to generate ideas, outlines, or structures, while the submitted content remains the student's own.
- Level 3: AI as Editor/Feedback Tool. AI may support improvements in style, structure, or coding, but should not replace substantive revision.
- Level 4: AI for Partial Content Generation. AI may be used to generate defined parts of an assignment, subject to disclosure and the student's critical evaluation and integration of the output.
- Level 5: Full, Transparent Integration. More extensive AI use is permitted within clearly defined instructional requirements and with appropriate transparency.

The framework illustrates how policy can move beyond binary permission or prohibition and allow AI use to be aligned with particular learning and assessment objectives (Utrecht University, 2025).

AI Access and Equity: Equity was explicitly recognized as a concern in 22 of the 29 cases. Policies noted differences in access to advanced AI tools, reliable internet connectivity, and the skills needed to use these technologies effectively (National University of Singapore, 2025). Institutional responses included providing access to licensed AI tools, maintaining campus-based access, offering alternative assessment arrangements, and

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

embedding AI literacy opportunities within education and support services (Australian National University, 2024).

Skeptical Stance on AI Content Detection: Several institutions expressed caution about treating automated AI-text detection as definitive evidence of misconduct. The University of Tokyo, for example, emphasizes the limitations of detection-based approaches and the importance of dialogue and process-oriented learning, while NUS guidance similarly cautions against relying solely on detection tools (University of Tokyo, 2023; National University of Singapore, 2025). This pattern is consistent with the broader emphasis on preventive and pedagogical approaches identified in the sample.

Focus on Faculty Development: Faculty support was also a recurring feature of the policies examined. This included guidance on responsible AI use, examples of transparency statements, workshops on assessment redesign, and resources for sharing practices (Harvard University, 2025). These measures indicate that implementation is addressed not only through rules for students but also through institutional support for instructors.

Discussion

Interpreting the Archetypes: Policy as a Reflection of Context

The four dominant archetypes appear to be associated with different regulatory and institutional contexts represented in the sample. The North American Risk-Management Model is consistent with a higher education environment characterized by complex federal and provincial/state data privacy requirements (e.g., FERPA in the United States and provincial privacy legislation in Canada). The European Ethical-Framework Model is likewise consistent with the region's rights-based regulatory environment, exemplified by the EU's GDPR and AI Act (Regulation (EU) 2024/1689), alongside the UK's data protection regime and Switzerland's Federal Act on Data Protection (FADP). The Dialogic & Flexible Model may be consistent with context-specific traditions of relational trust, instructor autonomy, and consensus-building, although these contextual influences were not directly tested in this study. The Empowerment & Literacy-First Model, predominant in Oceania, is consistent with a strong emphasis on AI literacy, skills development, and institutional capacity building.

This variation underscores that there is no "one-size-fits-all" policy template. Effective policy must be context-aware, taking account of local regulatory pressures, institutional structures, and educational practices. Moreover, the emerging models observed in China/East Asia, the Middle East, Africa, and Latin America, together with the hybrid cases identified in North America, suggest that regulatory contexts, institutional resources, and equity considerations may be associated with distinct policy configurations that are not fully captured by the four dominant archetypes.

The Emergence of "Post-Plagiarism" Academic Integrity

The recurrent presence of Transparency, Accountability, and Critical Thinking across the sampled policies is consistent with the broader shift in academic integrity debates associated with what Eaton (2023) has termed "Postplagiarism." Eaton (2023) conceptualizes postplagiarism as a broader integrity environment in which advanced technologies challenge conventional assumptions about authorship, originality, and human agency. Within the present sample, this shift is reflected in greater emphasis on proactive

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

disclosure, critical engagement with sources (including AI), and the demonstration of independent cognitive work.

This redefinition has important implications. It moves integrity beyond a solely prohibitive focus toward a more practice-based emphasis on transparent and critical engagement. It demands new literacies from students (AI literacy, critical evaluation literacy, disclosure literacy) and new pedagogical skills from faculty (designing for critical thinking and facilitating discussions on AI ethics). The caution expressed by several institutions regarding AI-detection tools is consistent with this shift, particularly where policies emphasize process-oriented assessment and human judgment. Integrity is therefore addressed through pedagogy and culture as well as through formal rules.

The Utrecht Spectrum: A Bridge Between Policy and Pedagogy

The Utrecht 5-Level Framework illustrates how abstract policy principles can be translated into a practical, pedagogically differentiated structure. Its tiered design may offer a useful reference for institutions seeking to differentiate permissible AI use according to learning objectives (Utrecht University, 2025).

Proposing a Tripartite Adaptive Governance Framework for Global Higher Education

Synthesizing the global analysis, we propose a Tripartite Adaptive Governance Framework (Figure 1) as a flexible model for HEIs and, conceptually, for broader higher education systems. The framework advocates coherent action across three interconnected levels. Although illustrated conceptually at the system level, it is derived primarily from the comparative analysis of university-level policies and should therefore be regarded as a proposed model rather than an empirically validated national governance framework.

The Strategic-Infrastructural Level (Macro):

This level involves senior leadership (university executives, national ministries) and focuses on creating enabling conditions. Key actions include: (a) Developing a principle-based institutional or national charter that endorses core values (transparency, accountability, critical thinking) and mandates local policy development, moving from ad-hoc reactions to strategic governance. (b) Investing in secure, equitable digital infrastructure, which may involve providing institutionally-licensed AI tools to ensure data security and bridge access gaps. (c) Allocating dedicated resources for digital equity to prevent the "AI divide" from exacerbating existing inequalities.

The Operational-Pedagogical Level (Meso):

This level involves university administrations, teaching centers, and IT departments, focusing on translation and capacity building. Key actions include: (a) Supporting academic units in developing contextualized, discipline-specific implementation guidelines, utilizing flexible tools like the Utrecht Spectrum to accommodate diverse pedagogical needs. (b) Launching comprehensive faculty development programs on AI-augmented teaching and assessment redesign, building essential pedagogical capacity. (c) Establishing dedicated AI

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

support units to offer technical, pedagogical, and ethical guidance to the academic community.

The Cultural-Ethical Level (Micro):

This level, enacted in classrooms and through curriculum, focuses on cultivating shared norms and competencies. Key interventions include: (a) Embedding AI literacy into the core curriculum or orientation programs, creating critically informed users. (b) Institutionalizing a standardized transparency protocol (e.g., an AI Use Declaration) for all submitted work, normalizing ethical disclosure. (c) Fostering communities of practice among educators to share resources, experiences, and innovative practices, building sustainable, bottom-up expertise.

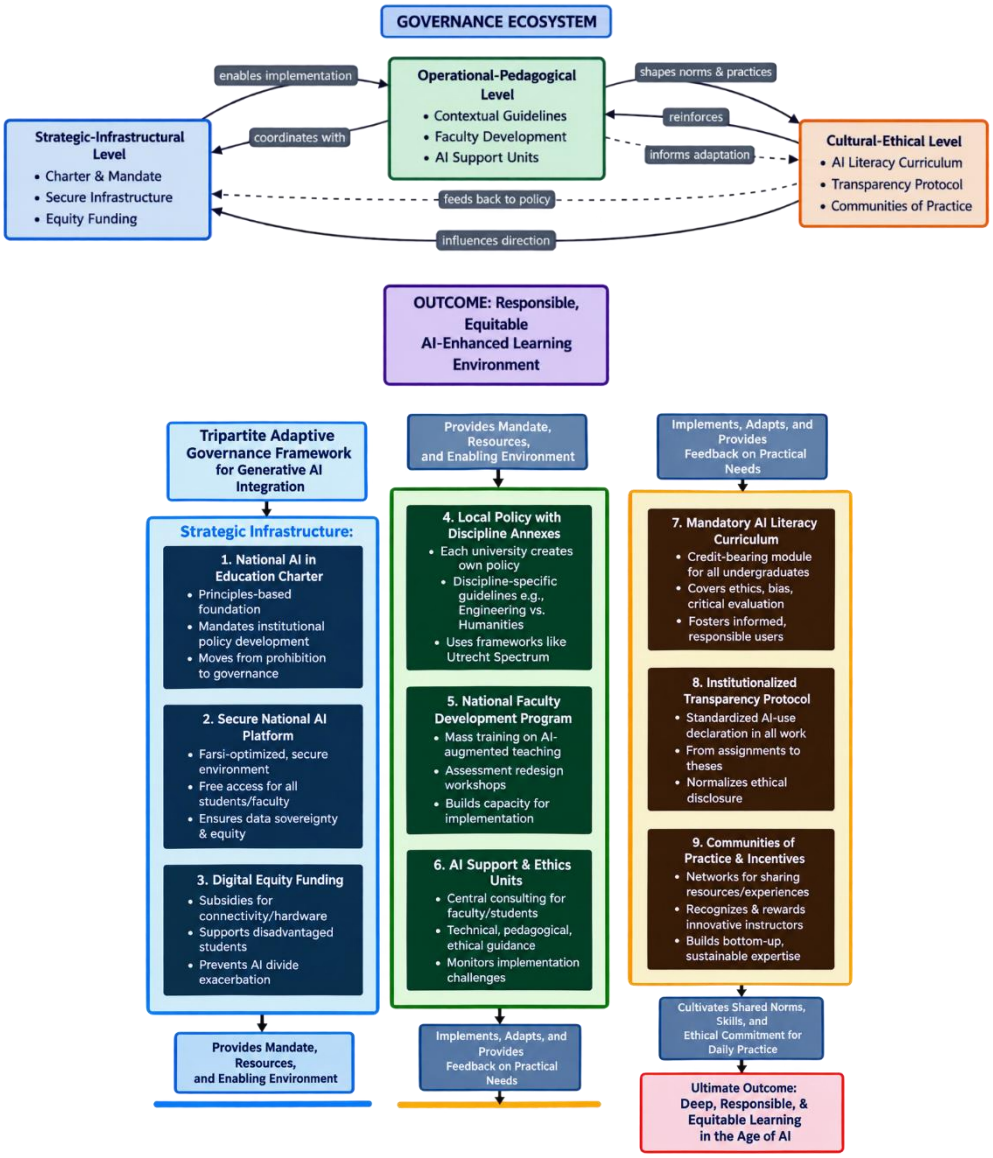


Figure 1. The proposed Tripartite Adaptive Governance Framework for integrating Generative AI in higher education systems. Illustrated conceptually at the system level, the framework shows the dynamic interaction and mutual reinforcement among the strategic-infrastructural (macro), operational-pedagogical (meso), and cultural-ethical (micro) levels. The same tripartite structure applies at the institutional level, with the strategic

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

level focusing on university-wide charters and infrastructure, supporting responsible, equitable, and pedagogically sound GenAI adoption.

The framework's utility lies in its adaptive nature; it does not prescribe a single policy but provides a structure for designing a coherent, multi-level response that can be tailored to different institutional sizes, types, and regional contexts. The dynamic interaction between the levels ensures that strategic vision is linked to operational support and grounded in cultural practice. The ultimate outcome—deep, responsible, and equitable learning in the age of AI—is consistent across contexts, even as the specific mechanisms vary.

Implications for Diverse Contexts

The identified archetypes and the proposed framework hold significant implications for HEIs in various contexts. For systems with strong central governance, elements of the Ethical-Framework and Empowerment models may offer valuable insights. For institutions valuing academic autonomy, the Dialogic and Flexible model provides a compelling approach. The recurrent principles of transparency, accountability, and critical thinking provide important foundations for GenAI governance, although their prevalence and operationalization vary across institutions. The challenge for each institution is to intelligently hybridize these global insights into a locally resonant and effective policy ecosystem. Institutions in regions with emerging or hybrid models-such as China/East Asia, the Middle East, Africa, and Latin America-may find that these approaches offer valuable lessons about equity, national alignment, and contextual adaptation.

Conclusion and Implications

This study has provided a systematic comparative analysis of institutional GenAI policies and guidance across 29 leading universities, revealing a landscape of strategic differentiation alongside substantial convergence around several governance principles. The identification of four dominant policy archetypes demonstrates the range of approaches represented in the sample, while the emerging and hybrid cases show that institutional policy configurations may extend beyond these four models. Emerging approaches were identified in China/East Asia, the Middle East, Africa, and Latin America, while hybrid cases were observed in North America. These variations suggest that regulatory contexts, institutional resources, and equity considerations may be associated with distinct approaches to GenAI governance. The high prevalence of Mandatory Transparency, Ultimate Human Accountability, and Preservation and Cultivation of Critical Thinking across the sampled universities indicates a recurring cross-institutional pattern in contemporary GenAI governance. These principles provide a useful reference point for further comparative and empirical research, although their broader applicability beyond the present sample requires additional investigation. This research contributes an empirically grounded comparative typology of GenAI governance in higher education and extends discussion of technology policy and academic integrity. The proposed Tripartite Adaptive Governance Framework further provides a conceptual basis for designing coordinated, multi-level policy responses that can be adapted to different institutional and regional contexts.

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

For Institutional Leaders:

Move from reactive responses toward proactive, enabling governance. Develop principle-based policies, invest in faculty development and equitable infrastructure, and foster a culture of responsible innovation. Recognize that no single archetype applies uniformly across contexts; instead, combine relevant elements of different models according to institutional needs and conditions.

For Faculty and Instructors:

Embrace the role of learning designer. Clearly communicate AI-use expectations for each course, redesign assessments to support critical thinking, and engage students in dialogue about responsible AI use and ethics. Flexible tools such as the Utrecht 5-Level Spectrum can help align permissible AI use with specific learning objectives.

For Students:

Develop critical AI literacy and transparent practices of AI use. Evaluate AI-generated content carefully, verify its accuracy and limitations, and use AI as a support for rather than a substitute for independent thinking and learning.

The rise of Generative AI marks an important period of re-examination for higher education, particularly in relation to teaching, learning, assessment, and academic integrity. The findings suggest that the universities examined are responding by developing governance approaches that seek to balance innovation with transparency, human accountability, critical thinking, and equity. Rather than implying a single path toward GenAI adoption, the findings support the value of adaptive and context-sensitive governance. By drawing on the experiences of the institutions examined and aligning policy, pedagogy, capacity building, and equity considerations, higher education institutions can develop governance arrangements that support responsible and meaningful engagement with GenAI.

Limitations and Future Research

This study has limitations that also chart a course for future research. First, as a document analysis, it captures intent and formal structure but not implementation efficacy. Future ethnographic and interview-based research is needed to study how these policies are enacted, resisted, or adapted in real classrooms in different global contexts. Second, the sample's elite bias means the models may not reflect challenges at teaching-focused, liberal arts, or resource-constrained institutions globally. To partially mitigate this bias, the sample deliberately included institutions from the Middle East, Africa, and Latin America, which are often underrepresented in comparative studies of higher education policy. Comparative studies across different types of institutions are vital. Third, the four archetypes identified are dominant models but do not exhaust the full range of policy approaches; emerging and hybrid models extend beyond them, particularly in cases with different regulatory, institutional, and cultural contexts, and these deserve further systematic investigation. Fourth, the proposed framework, while evidence-based, is a conceptual model requiring piloting, evaluation, and iterative refinement in diverse institutional settings. Finally, longitudinal studies are needed to track the evolution of these policies and their long-term impact on learning outcomes, skill development, and equity.

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

Declaration of Conflicting Interests

We have no conflicts of interest to disclose.

Funding

This research received no external or internal funding.

Human Participants

This study did not include human participants. It relied exclusively on publicly available institutional policy documents from 29 leading universities. No ethical approval or informed consent was required. All ethical guidelines were considered by the authors and are in alignment with the authors' affiliated university.

Originality Note

This manuscript presents original research conducted by the authors. This work has not been published previously and is not under consideration for publication elsewhere.

Use of Generative AI/ AI-assisted Technologies Statement

The authors confirm that DeepSeek was used in this research solely for the purpose of improving the language of the manuscript. No further use of these technologies was made by the authors to write different parts of the research.

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

References

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

Australian National University. (2024). Guide for students: best practice when using Generative AI. https://www.anu.edu.au/students/academic-skills/referencing-and-academic-integrity/academic-integrity-best-practice/guide

Australian National University. (2025). ANU institutional AI principles. https://learningandteaching.anu.edu.au/resources/anu-institutional-ai-principles/

Charmaz, K. (2015). Teaching theory construction with initial grounded theory tools: A reflection on lessons and learning. *Qualitative Health Research, 25*(12), 1610–1622. https://doi.org/10.1177/1049732315613982

Cornell University. (2025). Generative Artificial Intelligence for Education and Pedagogy. https://teaching.cornell.edu/sites/default/files/2024-01/Cornell-GenerativeAIForEducation-Report_2.pdf

Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2023). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International, 60*(2), 153–165. https://doi.org/10.35542/osf.io/mrz8h

Dwivedi, Y. K., Kshetri, N., Hughes, L., et al. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. International Journal of Information Management, 71, Article 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

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

ETH Zurich. (2024, December). Generative AI in teaching & learning: Guidelines. https://ethz.ch/content/dam/ethz/main/eth-zurich/education/ai_in_education/Generative%20AI%20in%20Teaching%20and%20Learning%20-%20Guidelines%20ETH.pdf

ETH Zurich. (2025). Information security and artificial intelligence (AI): Guide for users of AI at ETH Zurich. https://ethz.ch/content/dam/ethz/associates/services/News/service-news/2025/09/250923-ki-leitfaden/ETH-InfoSec-AI-Guide-EN.pdf

European Union. (2024). Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (AI Act). Official Journal of the European Union, L 1689. https://eur-lex.europa.eu/eli/reg/2024/1689/oj

Fereday, J., & Muir-Cochrane, E. (2006). Demonstrating rigor using thematic analysis: A hybrid approach of inductive and deductive coding and theme development. *International Journal of Qualitative Methods, 5*(1), 80–92. https://doi.org/10.1177/160940690600500107

Harvard University Office of the Provost. (2023). Guidelines for using ChatGPT and other generative AI tools at Harvard. Retrieved September 25, 2025, from https://provost.harvard.edu/guidelines-using-chatgpt-and-other-generative-ai-tools-harvard

Harvard University. (2025). Work with Generative AI. https://www.harvard.edu/ai/work-resources/

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence, 1*(9), 389–399. https://doi.org/10.1038/s42256-019-0088-2

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., Stadler, M., Weller, J., Kuhn, J., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

King Saud University. (2025). Guidelines for the use of generative artificial intelligence in education (Version 1.0). Artificial Intelligence Office. https://aio.ksu.edu.sa/sites/aio.ksu.edu.sa/files/attach/٢٠٢٥-٠٣-٢٠%٢٠١,٠%٢٠التعليم%٢٠في%٢٠التوليدى%٢٠الاصطناعي.pdf

Li, M., Xie, Q., Enkhtur, A., Meng, S., Chen, L., Yamamoto, B. A., Cheng, F., & Murakami, M. (2026). A framework for developing university policies on generative AI governance: A cross-national

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

comparative study. *Studies in Higher Education*. https://doi.org/10.1080/03075079.2026.2696496

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (pp. 1–16). Association for Computing Machinery. https://doi.org/10.1145/3313831.3376727

Massachusetts Institute of Technology. (2025). Guidance for use of generative AI tools. https://ist.mit.edu/ai-guidance

McGill University. (2025). Guidelines on using generative AI in research. Graduate and Postdoctoral Studies. https://www.mcgill.ca/gps/students/policies-and-guidelines/guidelines-using-generative-ai-research

MIT Information Systems & Technology. (2025). Guidance for use of Generative AI tools . https://ist.mit.edu/ai-guidance

Monash University. (2025). Artificial Intelligence Operations Policy (V1.0). Policy Bank. https://publicpolicydms.monash.edu/Monash/documents/2904420

National University of Singapore. (2025). AI Tools for Information Discovery: AI Guidelines. https://libguides.nus.edu.sg/aiinformationdiscovery/aiguidelines

NUS Department of History. (2025, August). Guiding principles on generative AI use AY2025-2026. https://fass.nus.edu.sg/hist/wp-content/uploads/sites/7/2025/08/HY_Guide-to-Use-of-AI-Tools_Aug2025.pdf

Parker, L., Loper, A. J., Hayes, J., Karakas, A., White, S., & Hallman, H. (2025). Comparative analysis of artificial intelligence policies in universities across five countries. *Discover Computing, 28*(1). https://doi.org/10.1007/s10791-025-09745-5

Patton, M. Q. (2015). *Qualitative research & evaluation methods* (4th ed.). Sage.

Peking University. (2024). *Guide to the boundaries of AI applications in higher education 1.0*. Department of Information Management, Peking University. https://www.im.lb.pku.edu.cn/xwgg/xgxw/50122im383987.htm

Popenici, S. A. D., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning, 12*(1), Article 22. https://doi.org/10.1186/s41039-017-0062-8

Saito, H. (2024). Representations of students in university statements on generative AI use: The case of the University of Tokyo. *Journal of the Japan Association for Media English Studies, 14*(1), 55–67. https://www.jstage.jst.go.jp/article/james/14/1/14_55/_article/-char/ja

Seoul National University. (2025). Seoul National University AI Guidelines. Office of Research Affairs. https://snurnd.snu.ac.kr/?q=board/bd011/view/12792

Slaughter, S., & Rhoades, G. (2009). *Academic capitalism and the new economy: Markets, state, and higher education*. Johns Hopkins University Press.

Stanford University Information Technology. (2025). AI Playground: The safer AI platform for the Stanford community. Retrieved September 25, 2025, from https://uit.stanford.edu/news/ai-playground-safer-ai-platform-stanford-community

Stanford University. (2025). Generative AI policy guidance. Office of Community Standards. https://communitystandards.stanford.edu/generative-ai-policy-guidance

Sullivan, M., Kelly, A., & McLaughlan, P. (2023). ChatGPT in higher education: Considerations for academic integrity and student learning. *Journal of Applied Learning & Teaching, 6*(1). https://doi.org/10.37074/jalt.2023.6.1.17

Technical University of Munich. (2025). TUM issues a comprehensive AI strategy. https://www.tum.de/en/news-and-events/all-news/press-releases/details/tum-issues-a-comprehensive-ai-strategy

The Chinese University of Hong Kong. (n.d.). Honesty in academic work: A guide for students and teachers. https://www.cuhk.edu.hk/policy/academichonesty/[reference:3]

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

The University of Queensland. (2025). Access AI Student Hub. UQ Library. https://web.library.uq.edu.au/study-and-learning-support/access-ai-student-hub

Tsinghua University. (2025). Tsinghua University Guiding Principles for the Application of Artificial Intelligence in Education. https://www.tsinghua.edu.cn/info/1176/122770.htm

UNESCO. (2023). Guidance for generative AI in education and research. United Nations Educational, Scientific and Cultural Organization.

Universidade de São Paulo. (2025). Portaria GR Nº 9004, de 10 de Março de 2026 5. Legislação USP. https://leginf.usp.br/portarias/portaria-gr-no-9004-de-10-de-marco-de-2026/

University of British Columbia. (2025). Principles for GenAI in teaching & learning. https://it.ubc.ca/sites/it.ubc.ca/files/GenAi_Principles_Guidelines_v2.pdf

University of Cambridge. (2025). Artificial Intelligence (AI). Education Quality and Policy Office. https://www.educationalpolicy.admin.cam.ac.uk/plagiarism-and-academic-misconduct/artificial-intelligence-ai

University of Cape Town. (2025). UCT Framework for Artificial Intelligence in Education: Generative and Other AI in Teaching, Learning and Assessment. https://cilt.uct.ac.za/sites/default/files/media/documents/cilt_uct_ac_za/2486/uct-ai-in-education-framework-june-2025-final.pdf

University of Edinburgh. (2025). Guidance for students and staff on AI use. https://www.ed.ac.uk/ai/guidance

University of Jordan. (2025). Instructions for the use of artificial intelligence tools at the University of Jordan. https://units.ju.edu.jo/ar/legalaffairs/regulations.aspx#44

University of Melbourne. (2025). GenAI at Melbourne. https://students.unimelb.edu.au/academic-skills/study-skills/learning-with-genai/GenAI-at-Melbourne

University of Melbourne. (2025). GenAI hub. https://www.unimelb.edu.au/tli/lda/genai-hub

University of Oxford. (2025a). Guidance on the safe and responsible use of generative AI. https://www.ox.ac.uk/students/life/it/guidance-safe-and-responsible-use-gen-ai-tools

University of Oxford. (2025b, August). Policy for using Generative AI in Research: Guidelines for researchers and professional staff (Version 1.0). Research Strategy and Policy Unit, Research Services. https://ora.ox.ac.uk/objects/uuid:aeb78629-d914-48e3-b924-71d4f2bf412f

University of Oxford. (2025c). Expert Comment: Flying blind into the AI age. Retrieved September 25, 2025, from https://www.ox.ac.uk

University of Sydney. (2025). Artificial intelligence. Academic integrity. https://www.sydney.edu.au/students/academic-integrity/artificial-intelligence.html

University of Tokyo. (2023, May 26). To students of the University of Tokyo: Regarding the use of AI tools in classes (Version 1.0). https://utelecon.adm.u-tokyo.ac.jp

University of Tokyo. (2024, April). Results of the survey on generative AI provision policy. https://utelecon.adm.u-tokyo.ac.jp/notice/2024/04-aichat-survey-result/

University of Tokyo. (2025). Policies and guidelines. utelecon. https://utelecon.adm.u-tokyo.ac.jp/en/docs/

University of Toronto. (2025). AI Task Force and guidelines. https://ai.utoronto.ca/guidelines/

Utrecht University. (2025). AI index for students. Retrieved September 25, 2025, from https://www.uu.nl/en/organisation/ai-policy/students/ai-index

Utrecht University. (2025). AI policy. https://www.uu.nl/en/organisation/ai-policy

Veale, M., & Zuiderveen Borgesius, F. (2021). Demystifying the draft EU Artificial Intelligence Act. *Computer Law Review International, 22*(4), 97–112. https://doi.org/10.9785/cri-2021-220402

Wang, H., Dang, A., Wu, Z., & Mac, S. (2024). Generative AI in higher education: Seeing ChatGPT through universities' policies, resources, and guidelines. *Computers and Education: Artificial Intelligence, 7*, 100326. https://doi.org/10.1016/j.caeai.2024.100326

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

Williamson, B., & Eynon, R. (2020). Historical threads, missing links, and future directions in AI in education. *Learning, Media and Technology, 45*(3), 223–235. https://doi.org/10.1080/17439884.2020.1798995

Yin, R. K. (2018). *Case study research and applications: Design and methods* (6th ed.). Sage.

Yonsei University. (2025). Research Ethics Guidelines for the Use of Generative AI. https://git.yonsei.ac.kr/git/news/academic.do?mode=view&articleNo=448424

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – Where are the educators? International Journal of Educational Technology in Higher Education, 16, Article 39. https://doi.org/10.1186/s41239-019-0171-0

Dr. Akram Hosseini is an Associate Professor in the Department of Architecture, Faculty of Architecture and Urbanism, Ferdowsi University of Mashhad, Iran. She holds a Ph.D. in Architecture and teaches courses on architectural design, urban design, and research methods. Her research interests include sustainable architecture, urban studies, AI in architectural education, and higher education policy. She has published in numerous journals and supervised a large number of graduate students. She is the corresponding author of this study and has led research on the integration of generative AI in higher education governance.

Ms. Elahe Khademzadeh is an M.Sc. student in the Faculty of Architecture at Berlin University of Applied Sciences (BHT), Berlin, Germany, where she is in her final year. She holds a B.Sc. in Architecture from the School of Architecture, College of Fine Arts, University of Tehran, Iran. Her research focuses on computational design, generative AI in architecture, sustainable urbanism, and AI policy in higher education. She has professional experience in architectural practice and contributes to research on the ethical and pedagogical implications of AI tools in design education.

[Downloaded from www.johepal.com on 2026-11-06]

[DOI: 10.66224/johepal.7.3.28]

This is an open access article distributed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0) which allows reusers to distribute, remix, adapt, and build upon the material in any medium or format for noncommercial purposes only, and only so long as attribution is given to the creator.