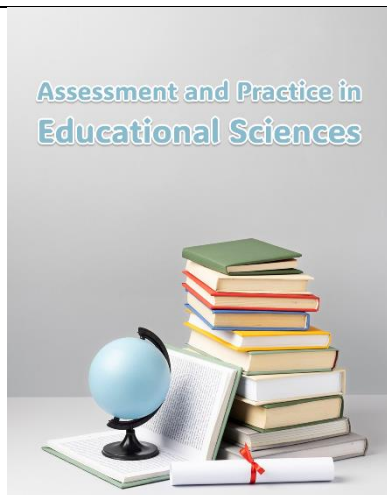




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Developing a Generative AI Governance Model in Higher Education and Scientific Research

ABSTRACT

Generative AI systems have entered universities fast. In just a few years, large language models and content-generation tools have reshaped how students learn, how researchers work, and how academic institutions manage knowledge. These tools offer real benefits—personalized learning, faster research cycles, and new analytical possibilities. They also raise hard questions about academic integrity, research originality, and data privacy. Yet most national higher education systems still lack a coherent governance framework. Responses tend to be reactive and fragmented. This study asks a simple question: What dimensions shape a generative AI governance model in higher education, and how can such a model be validated? The study is applied-developmental in purpose and uses an exploratory mixed-methods design. In the qualitative phase, ten experts sat for semi-structured interviews. Thematic analysis followed Braun and Clarke's six-step framework. Five dimensions emerged: academic ethics and integrity (24.4%), digital literacy and skill development (21.1%), strategic policymaking (20.0%), oversight and evaluation mechanisms (17.8%), and technical infrastructure and data security (16.7%). In the quantitative phase, 200 questionnaires were distributed; 155 valid responses were returned (77.5% response rate). Data were analyzed with PLS-SEM in SmartPLS 4. Construct validity was assessed through factor loadings, composite reliability, AVE, discriminant validity (Fornell-Larcker and HTMT), VIF, f^2 , Q^2 , and overall fit indices (SRMR, NFI). Findings confirm that five dimensions underpin generative AI governance: academic ethics and integrity, strategic policymaking, oversight and evaluation mechanisms, digital literacy and skill development, and technical infrastructure and data security. Academic ethics had the strongest effect ($\beta = 0.364$), followed by strategic policymaking ($\beta = 0.302$). The model explained 62% of variance in higher education effectiveness ($R^2 = 0.62$; $Q^2 = 0.41$). All five structural paths were significant. Fit indices (SRMR = 0.062; NFI = 0.912) confirmed good model fit. Multi-group analysis found significant differences between public and non-profit universities in technical infrastructure.

Keywords: generative artificial intelligence; higher education governance; academic ethics; strategic policymaking; digital literacy; data security; structural equation modeling.

Introduction

Higher education is undergoing a technological transition in which artificial intelligence is no longer confined to specialized computational research but has become embedded in teaching, learning, assessment, scholarly communication, and institutional decision-making. Although artificial intelligence has influenced education for several decades through adaptive learning systems, automated assessment, intelligent tutoring, learning analytics, and predictive modeling, the emergence of generative

artificial intelligence (GenAI) has fundamentally altered the scale and character of this relationship. Historical analyses of artificial intelligence in education demonstrate that technological change has repeatedly been accompanied by shifts in assumptions regarding knowledge, expertise, teaching, and institutional authority; however, generative systems differ from many earlier applications because they can independently produce apparently original text, images, code, explanations, summaries, and analytical outputs in response to natural-language instructions (1). Large language models and conversational agents have consequently moved from being specialized technologies to accessible academic tools that can participate directly in activities traditionally regarded as intellectual work. This transformation has stimulated debate about whether conventional understandings of intelligence, authorship, creativity, and learning remain adequate when human reasoning increasingly occurs in interaction with algorithmic systems (2). The significance of this development is particularly pronounced in universities, where knowledge production, evaluation, transmission, and certification constitute central institutional functions. Generative AI therefore presents not merely a technological innovation but a governance problem requiring universities to reconsider how technological capabilities can be incorporated while preserving the legitimacy, reliability, and ethical foundations of higher education. The manuscript on which the present study is based similarly conceptualizes GenAI governance as a multidimensional problem involving academic ethics, policymaking, oversight, digital competence, and technological infrastructure rather than as a narrowly technical issue.

The opportunities associated with generative AI partly explain the extraordinary speed of its diffusion within academic environments. Conversational AI can provide immediate explanations, summarize complex materials, support idea generation, assist language learning, generate programming code, facilitate formative feedback, and enable learners to obtain individualized assistance outside conventional classroom schedules. Reviews of ChatGPT and related systems suggest that such technologies may increase accessibility, responsiveness, and personalization while helping instructors automate routine activities and redirect attention toward higher-level instructional responsibilities (3). Their potential is also evident in science education, where generative tools can support problem formulation, conceptual explanation, simulation-oriented reasoning, coding, and interactive exploration of scientific ideas (4). Evidence from informal digital language learning similarly indicates that AI-supported learning environments can contribute to proficiency, motivation, and self-regulatory processes when technologies are appropriately integrated into learning activities (5). More broadly, AI-based assistants may transform user competence itself by requiring learners and academics to develop capacities that exceed conventional digital literacy, including the ability to communicate effectively with intelligent systems, critically evaluate algorithmic outputs, recognize limitations, and determine when human judgment should supersede automated recommendations (6). These possibilities have generated substantial interest in the strategic integration of generative AI into higher education rather than its simple exclusion. Chiu argues that future transformation requires moving beyond isolated experimentation toward systematic research, curriculum redesign, staff development, institutional capacity building, and responsible implementation strategies (7). Thus, the central challenge for universities is increasingly not whether generative AI will be used, but under what institutional conditions its use can contribute to educational and scientific objectives.

The research environment has been affected just as profoundly. Generative systems can assist researchers in searching for concepts, refining research questions, summarizing literature, drafting preliminary text, translating academic material, developing computer code, organizing qualitative information, and communicating scientific findings. Such capabilities potentially shorten research cycles and lower technical barriers to participation in certain research activities. Lund and Wang anticipated that ChatGPT-like systems would substantially influence academic information practices and library services because their conversational interfaces blur traditional distinctions among search, synthesis, content generation, and reference assistance (8). Similarly, multidisciplinary analyses have highlighted potential improvements in productivity, knowledge

accessibility, ideation, communication, and decision support while simultaneously emphasizing that these advantages are inseparable from questions concerning reliability, accountability, transparency, and professional responsibility (9). Research conducted on AI-generated scientific abstracts illustrates the complexity of these changes: human reviewers may have difficulty reliably distinguishing machine-generated scientific writing from authentic academic text, demonstrating that surface fluency cannot be treated as evidence of genuine scholarly authorship or scientific validity (10). The rapid incorporation of generative systems into science has therefore created a new epistemic environment in which researchers must distinguish assistance from substitution and linguistic sophistication from evidential quality (11). The resulting governance challenge extends beyond regulating a particular software application; universities must establish standards for disclosure, authorship, verification, accountability, intellectual contribution, data use, and acceptable levels of AI assistance throughout the research process.

Academic integrity represents one of the most immediate areas of concern. Conventional academic integrity frameworks were largely designed around misconduct such as plagiarism, unauthorized collaboration, fabrication, falsification, and contract cheating. Generative AI complicates these categories because a student may produce syntactically original material without directly copying an identifiable source while contributing little independent intellectual effort. Cotton and colleagues emphasize that generative AI requires institutions to reconsider assessment design and academic integrity policies because traditional detection-centered approaches cannot adequately address forms of assistance that are difficult to observe and may vary substantially in educational legitimacy (12). Perkins similarly argues that large language models create substantial challenges for academic integrity in the post-pandemic university because existing policies often fail to distinguish acceptable support from inappropriate outsourcing of intellectual work (13). The problem also affects the meaning of assessment itself. If conventional written assignments can be generated rapidly by conversational systems, their capacity to demonstrate student knowledge, reasoning, and authorship becomes uncertain, prompting questions about whether established assessment practices remain educationally defensible (14). Sullivan and colleagues therefore emphasize the need to align responses to generative AI with both integrity and learning objectives rather than approaching the issue exclusively as technological misconduct (15). A governance model must consequently establish transparent expectations regarding permissible and prohibited uses, documentation of AI assistance, responsibility for submitted work, methods of authentic assessment, and procedures for suspected violations.

Ethical governance, however, extends substantially beyond academic misconduct. Generative systems may produce inaccurate, fabricated, biased, discriminatory, or contextually inappropriate outputs while presenting such material in persuasive language. Users who lack sufficient knowledge may consequently attribute unwarranted authority to algorithmic responses. Ethical concerns also include privacy, surveillance, intellectual property, unequal access, transparency, algorithmic bias, accountability, and the possibility that commercial AI systems may influence academic practices through opaque technological infrastructures (16). Kooli argues that educational chatbots create ethical challenges that cannot be resolved solely through technical improvements, because their responsible use requires institutional standards regarding privacy, transparency, fairness, accountability, and human agency (17). Tlili's examination of ChatGPT similarly demonstrates the dual character of educational chatbots: the same technology may function as a productive educational assistant or introduce significant risks depending on how it is implemented, monitored, and understood (18). Opara and colleagues identify comparable tensions between the potential benefits of ChatGPT for teaching, learning, and research and concerns involving misinformation, dependency, ethics, and appropriate pedagogical use (19). Accordingly, responsible governance cannot be reduced to preventing cheating; it must create an ethical architecture within which innovation occurs under explicit principles of human responsibility, fairness, transparency, privacy, and scientific reliability.

Another fundamental concern involves human cognition and the educational meaning of learning. Generative AI can support intellectual activity, but excessive reliance may replace rather than augment important cognitive processes. Grassini warns that the educational consequences of AI depend on how these systems alter learner engagement, critical thinking, autonomy, and the relationship between technological convenience and genuine intellectual development (20). When students routinely delegate idea generation, interpretation, synthesis, and writing to generative systems, academic products may improve superficially while underlying competencies remain underdeveloped. This issue is closely connected with AI literacy. Responsible users must understand not only how to formulate effective prompts but also why outputs may be inaccurate, how training data may embed biases, why models can hallucinate information, how evidence should be verified, and where ethical boundaries should be drawn. Rahman and Watanobe therefore describe generative AI as simultaneously offering major opportunities and threats, emphasizing that institutional strategies should combine technological integration with educational measures that preserve critical thinking and responsible research practice (21). A SWOT analysis by Farrokhnia and colleagues similarly identifies personalized learning, efficiency, and accessibility as strengths or opportunities while highlighting weaknesses and threats such as unreliable information, bias, overdependence, integrity violations, and insufficient regulation (22). Effective governance thus requires capacity building among students, faculty members, researchers, administrators, and support personnel so that AI competence includes critical, ethical, and evaluative dimensions.

Institutional governance has become particularly important because individual users cannot independently resolve many of these challenges. Questions concerning what forms of AI use should be permitted in assessments, whether AI-generated language requires disclosure, how confidential research data may be processed, which platforms meet institutional privacy requirements, and how violations should be investigated require collective rules. UNESCO guidance stresses the importance of human-centered, age-appropriate, ethically responsible, and institutionally governed applications of generative AI in education and research, particularly in relation to data protection, human agency, inclusion, transparency, and capacity building (23). Yet university responses remain highly heterogeneous. Analysis of higher education policies indicates that institutions differ considerably in the specificity of their guidelines, the degree of restriction imposed, the responsibilities allocated to instructors and students, and the resources provided to support implementation (24). Luo's critical examination of GenAI policies in assessment further demonstrates that many institutional responses continue to rely on assumptions about originality that require reconsideration in environments where human and machine contributions can be intertwined (25). The challenge is therefore to move from reactive statements toward coherent governance systems that define principles, responsibilities, procedures, educational supports, monitoring arrangements, and mechanisms for policy revision.

Recent research has increasingly focused on the effectiveness and normative diversity of such institutional policies. Orfanidis demonstrates that university policies governing student use of generative AI embody different moral priorities and conceptions of responsibility, indicating that governance is shaped not merely by technological risk but by institutional values and educational philosophies (26). Jiang and colleagues likewise examine the effectiveness of institutional policies and regulations, suggesting that the existence of a policy alone is insufficient unless rules are understandable, legitimate, implementable, supported by institutional resources, and appropriately communicated to users (27). These findings reveal a crucial distinction between policy formulation and governance capacity. A university may formally prohibit certain AI practices while lacking reliable methods of detection, staff training, appeal procedures, or clarity concerning acceptable assistance. Conversely, institutions may encourage experimentation without adequately protecting personal information, unpublished findings, intellectual property, or confidential data. Governance must therefore connect strategic policymaking with oversight, capacity development, ethical standards, and technical safeguards. This interdependence is especially important because

generative technologies evolve more rapidly than conventional university regulations, meaning that static rules can become obsolete before implementation is fully institutionalized.

Data governance and technical infrastructure constitute another essential component. Most advanced generative systems are accessed through externally hosted platforms, meaning that users may inadvertently transmit sensitive educational, administrative, or research information outside institutional control. This creates risks involving confidentiality, cybersecurity, data ownership, commercial reuse, and compliance with privacy requirements. Technical governance must therefore address approved platforms, identity management, access controls, data classification, secure storage, cybersecurity protocols, local or institutionally controlled AI services, procurement requirements, and risk assessment. These issues are inseparable from educational equity. Historical research on AI in education has warned that technological innovation is shaped by social, institutional, and economic inequalities and may reproduce existing disadvantages when infrastructure and participation are unevenly distributed (1). Salas-Pilco and Yang's systematic review of AI applications in Latin American higher education similarly demonstrates the importance of institutional capacity, contextual conditions, technological resources, and regional inequalities in shaping the adoption of artificial intelligence (28). Therefore, a governance model must consider not only whether technology is secure but also whether students, researchers, and institutions possess equitable opportunities to benefit from it.

These global concerns are particularly consequential in higher education systems where emerging technologies are developing faster than regulatory adaptation. Technology governance requires coordination between national science and technology policies and institutional-level practices. In the Iranian context, analyses of university governance have emphasized that conventional structural arrangements may be insufficient when universities confront rapidly changing emerging technologies requiring flexible, interdisciplinary, and adaptive forms of decision-making (29). At the macro-policy level, Farajzadeh stresses the importance of coherent science and technology policy for emerging technologies, including appropriate upstream frameworks capable of directing institutional implementation (30). The absence of clear governance arrangements can produce inconsistent expectations among universities, faculties, researchers, and students, while excessive centralization may prevent institutions from responding to discipline-specific conditions. Generative AI consequently requires governance at multiple levels: national principles can establish common ethical and legal standards, while universities require sufficient operational flexibility to formulate discipline-sensitive procedures, provide training, select secure technologies, monitor use, and regularly revise institutional guidance.

The literature nevertheless remains fragmented in an important respect. Existing studies have provided valuable analyses of educational benefits (3), science learning (4), digital competence (6), academic integrity (12), assessment redesign (14), ethical considerations (16), chatbot governance (17), institutional policies (24), international policy diversity (26), regulatory effectiveness (27), educational transformation (7), and the broader societal implications of generative systems (9). Yet these dimensions are frequently examined separately, despite their practical interdependence. Ethical principles without enforceable policy may remain aspirational; policy without oversight may be ineffective; oversight without AI literacy may generate resistance or misuse; literacy without secure infrastructure may encourage users to expose sensitive data; and infrastructure without ethical or strategic guidance may merely accelerate problematic practices. A more comprehensive perspective must therefore treat generative AI governance as an integrated institutional system in which normative, managerial, educational, supervisory, and technological dimensions mutually support responsible adoption. Such an approach also addresses the observation that the consequences of AI cannot be evaluated exclusively in terms of technical performance because institutional legitimacy, academic culture, professional norms, and human judgment remain central to higher education (2).

Accordingly, the present study conceptualizes effective generative AI governance through five interconnected dimensions: academic ethics and integrity, strategic policymaking, oversight and evaluation mechanisms, digital literacy and skill development, and technical infrastructure and data security. This framework responds to calls for universities to replace binary choices between unrestricted adoption and complete prohibition with adaptive forms of governance capable of supporting beneficial innovation while managing identifiable risks. It also recognizes that the effectiveness of governance must be empirically examined rather than inferred solely from normative policy recommendations. By integrating qualitative expert knowledge with quantitative validation, a governance framework can identify contextually relevant dimensions and determine their respective contributions to higher education effectiveness. Such an approach is especially pertinent in institutional environments where universities differ in resources, governance structures, technological readiness, and organizational capacity, because a validated multidimensional model can provide a more defensible foundation for strategic interventions than isolated guidelines or technology-specific rules.

Therefore, the aim of this study was to develop and empirically validate a comprehensive generative artificial intelligence governance model for higher education and scientific research based on the dimensions of academic ethics and integrity, strategic policymaking, oversight and evaluation mechanisms, digital literacy and skill development, and technical infrastructure and data security.

Methods and Materials

The study is applied-developmental in purpose. It uses a sequential exploratory mixed-methods design. The qualitative phase comes first. Its findings shape the quantitative phase and the empirical model test.

The study adopts a pragmatist approach. The focus is on the research problem and its practical consequences, not on defending a particular epistemological position. Both subjective expert data and objective statistical data are used.

Qualitative Phase. A systematic literature review and analysis of upstream documents produced an initial list of five dimensions. The qualitative population included experts, senior higher education administrators, and faculty proficient in modern AI technologies. They were selected through purposive sampling until theoretical saturation. Ten experts participated. They came from technical, legal, educational, ethical, and managerial backgrounds. Inclusion criteria were: a doctoral degree, at least five years of relevant experience, and publications in AI or higher education governance.

Quantitative Phase. The population included faculty members and researchers from universities and higher education institutions. Stratified random sampling was used. Strata were based on university type (public, Islamic Azad, non-profit) and academic rank (assistant professor, instructor). Proportional allocation was applied.

Table 1. Sample Allocation and Valid Responses by Stratum

Stratum	Sample Allocated	Valid Responses
Public Universities	80	63
Islamic Azad University	70	55
Non-Profit Institutions	50	37
Total	200	155

Response Rate. Of the 200 distributed questionnaires, 155 valid responses came back. That is a 77.5% response rate—acceptable for field research in the humanities.

Instrument. A researcher-developed questionnaire used a five-point Likert scale. It had 35 items across six constructs.

Table 2. Questionnaire Structure and Expert Review

Construct	Items	Expert Reviewers
Academic Ethics and Integrity	7	10

Digital Literacy and Skill Development	5	10
Strategic Policymaking	6	10
Oversight and Evaluation Mechanisms	6	10
Technical Infrastructure and Security	5	10
Higher Education Effectiveness (DV)	6	10
Total	35	—

Content validity was confirmed by ten experts. CVR was 0.62. CVI was 0.79. Both exceeded critical thresholds.

Sample Size. Sample size followed recent PLS-SEM recommendations (Hair et al., 2022). The old "10-times rule" is no longer accepted. For models with five independent variables, a minimum of 150–200 is recommended. The present sample of 155 falls within this range.

Qualitative Validation:

Credibility: Three strategies were used. First, four non-interviewed experts reviewed the findings and confirmed code-text alignment. Second, member checking was done: a summary was sent to each expert for final confirmation. Third, multiple data sources were triangulated (interviews, upstream documents, literature).

Transferability: Rich description of context, expert characteristics, and interview conditions supports transferability. The full analysis process was documented.

Dependability: Coding stages were fully recorded. Data were archived. Two methodological colleagues reviewed the process.

Confirmability: Reflective notes were kept. An external auditor independently reviewed the codes.

Quantitative Validity and Reliability. Content validity: CVR = 0.62, CVI = 0.79. Reliability: Cronbach's alpha > 0.80, CR > 0.86. Convergent validity: AVE > 0.50. Discriminant validity: Fornell-Larcker and HTMT both confirmed.

Qualitative Analysis: Thematic analysis followed Braun and Clarke's (2006) six-step framework: familiarization with data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the final report. MAXQDA 2022 was used. Thematic analysis differs epistemologically from grounded theory. Given the descriptive-exploratory aim and no need to generate new theory, thematic analysis was chosen.

Quantitative Analysis: Data were analyzed with SmartPLS 4 using the partial least squares approach. Reported indices include factor loadings, Cronbach's alpha, CR, AVE, Fornell-Larcker, HTMT, VIF, f^2 , Q^2 , R^2 , SRMR, NFI, path coefficients, t-values, and bootstrapping confidence intervals. PLS-MGA was run for group comparisons.

Findings and Results

Of the 155 respondents in the quantitative phase, 62% (96 individuals) held the rank of assistant professor. The remaining 38% (59 individuals) were instructors. Average years of university service was about 10.2 years—enough to ensure that opinions reflect real experience.

Table 3: Demographic Characteristics of Qualitative Phase Experts (n = 10)

No.	Expert Code	Specialization	Academic Rank / Position	Experience (Years)
1	E-1	AI and Higher Education	Assistant Professor / Department Head	18
2	E-2	IT Management	Instructor / Research Deputy	15
3	E-3	Science and Technology Policy	Assistant Professor / Advisor	22
4	E-4	Research Ethics	Assistant Professor / Ethics Committee Member	20
5	E-5	E-Learning	Instructor / Technology Center Director	12
6	E-6	Software Engineering	Assistant Professor / Faculty Member	14
7	E-7	Higher Education Economics	Assistant Professor / Dean	25

8	E-8	Technology Law	Instructor / Legal Advisor	16
9	E-9	Curriculum Planning	Assistant Professor / Graduate Studies Director	17
10	E-10	Educational Psychology	Instructor / Educational Advisor	13

The expert panel was deliberately diverse. Technical, legal, pedagogical, ethical, and managerial perspectives were all represented. Average experience was 17.2 years. Every expert agreed on one point: universities that lack a roadmap and codified regulations for generative AI will face serious problems. Research quality will decline. Text authenticity will be challenged. Intellectual property conflicts will multiply.

"E-1 observed: 'Generative AI tools are like a double-edged sword. They accelerate content production, but they also erode students' critical thinking. The line between authentic scholarship and machine-generated rewriting keeps getting blurrier.'"

"E-3 said: 'Without clear rules, professors are simply lost in how to grade AI-assisted papers. They don't know what's allowed and what isn't. We need a written policy—yesterday, not next year.'"

"E-8 warned: 'Our intellectual property laws were not written for this. A student can generate an entire thesis section with AI, and we currently have no reliable mechanism to detect it or to adjudicate the ownership of that content.'"

These quotes capture a shared sense of urgency—one that shaped the quantitative instrument that followed.

Table 4: Thematic Analysis Matrix of Expert Interviews

Main Category	Open Codes	Frequency	Percentage
Academic Ethics and Integrity	Redefining plagiarism, transparency of involvement, preventing modern cheating	22	24.4%
Digital Literacy and Skill Development	Training workshops, prompt engineering, faculty empowerment	19	21.1%
Strategic Policymaking	National AI document, revising promotion regulations, clarifying permissible limits	18	20.0%
Oversight and Evaluation Mechanisms	Audit committees, machine-content detection tools, revising bylaws	16	17.8%
Technical Infrastructure and Data Security	Local platforms, protecting confidential data, preventing information leakage	15	16.7%
Total	—	90	100.0%

Table 4 shows the coding results from the qualitative phase. Academic ethics and integrity had the highest frequency (22 repetitions, 24.4%). This is not surprising. The biggest fear in the academic community is that scientific text authenticity will be compromised, advanced cheating will spread, and the line between human thought and algorithmic production will disappear.

Digital literacy ranked second (19 repetitions, 21.1%). This suggests that many current problems stem from weak AI literacy among faculty and students. Strategic policymaking came third (18 repetitions, 20.0%), followed by oversight mechanisms (16 repetitions, 17.8%) and technical infrastructure (15 repetitions, 16.7%).

Table 5: Descriptive Statistics of Main Research Variables (n = 155)

Variable	Items	Mean	SD	Skewness	Kurtosis
Academic Ethics and Integrity	7	4.08	0.69	-0.60	0.44
Digital Literacy and Skill Development	5	3.68	0.81	-0.30	-0.12
Strategic Policymaking	6	3.82	0.74	-0.34	0.12
Oversight and Evaluation Mechanisms	6	3.75	0.76	-0.40	0.09
Technical Infrastructure and Security	5	3.52	0.88	-0.27	-0.18
Higher Education Effectiveness	6	3.88	0.72	-0.50	0.24

Every mean exceeds the scale midpoint (3). Academic ethics leads with 4.08. Technical infrastructure is lowest at 3.52—a sign that universities struggle most with local infrastructure and data protection. Skewness and kurtosis values all fall between -1.96 and +1.96, so the data are normally distributed.

Table 6: Validity and Reliability Assessment (n = 155)

Construct	Items	Cronbach's α (>0.7)	CR (>0.7)	AVE (>0.5)	VIF
Academic Ethics and Integrity	7	0.90	0.93	0.65	2.05
Digital Literacy and Skill Development	5	0.82	0.87	0.56	1.74
Strategic Policymaking	6	0.85	0.89	0.59	1.82
Oversight and Evaluation Mechanisms	6	0.83	0.88	0.57	1.91
Technical Infrastructure and Security	5	0.80	0.86	0.54	1.68
Higher Education Effectiveness	6	0.87	0.91	0.62	—

Cronbach's alpha values fall between 0.80 and 0.90. Composite reliability exceeds 0.86 for all constructs. AVE is above 0.54 across the board. VIF stays below 3, so multicollinearity is not a concern (Hair et al., 2022).

Table 7: Fornell-Larcker Matrix (n = 155)

Construct	1	2	3	4	5	6
1. Academic Ethics and Integrity	0.806					
2. Digital Literacy and Skill Development	0.486	0.748				
3. Strategic Policymaking	0.572	0.505	0.768			
4. Oversight and Evaluation Mechanisms	0.568	0.479	0.592	0.755		
5. Technical Infrastructure and Security	0.418	0.524	0.462	0.438	0.735	
6. Higher Education Effectiveness	0.685	0.578	0.648	0.625	0.512	0.787

The Fornell-Larcker criterion holds: diagonal values (square root of AVE) exceed off-diagonal correlations. All HTMT values remain below 0.85, confirming discriminant validity (Henseler et al., 2015).

Table8 : HTMT Matrix (n = 155)

Construct	1	2	3	4	5	6
1. Academic Ethics and Integrity	—					
2. Digital Literacy and Skill Development	0.54	—				
3. Strategic Policymaking	0.65	0.58	—			
4. Oversight and Evaluation Mechanisms	0.63	0.55	0.68	—		
5. Technical Infrastructure and Security	0.47	0.61	0.52	0.50	—	
6. Higher Education Effectiveness	0.76	0.65	0.72	0.71	0.58	—

Table 9: Bootstrapping Results and Effect Sizes (n = 155, 5000 subsamples)

Structural Path	β	SD	t-value	Lower CI	Upper CI	f ²	Result
Academic Ethics → Effectiveness	0.364	0.042	8.67	0.282	0.446	0.17	Significant
Strategic Policymaking → Effectiveness	0.302	0.045	6.71	0.214	0.390	0.11	Significant
Oversight Mechanisms → Effectiveness	0.274	0.046	5.96	0.184	0.364	0.09	Significant
Digital Literacy → Effectiveness	0.251	0.048	5.23	0.157	0.345	0.08	Significant
Technical Infrastructure → Effectiveness	0.186	0.050	3.72	0.088	0.284	0.05	Significant

All five structural paths have confidence intervals entirely above zero. Bootstrapping standard deviations hover around 0.046, indicating stable estimates and a robust structural model.

Table 10: Overall Model Fit

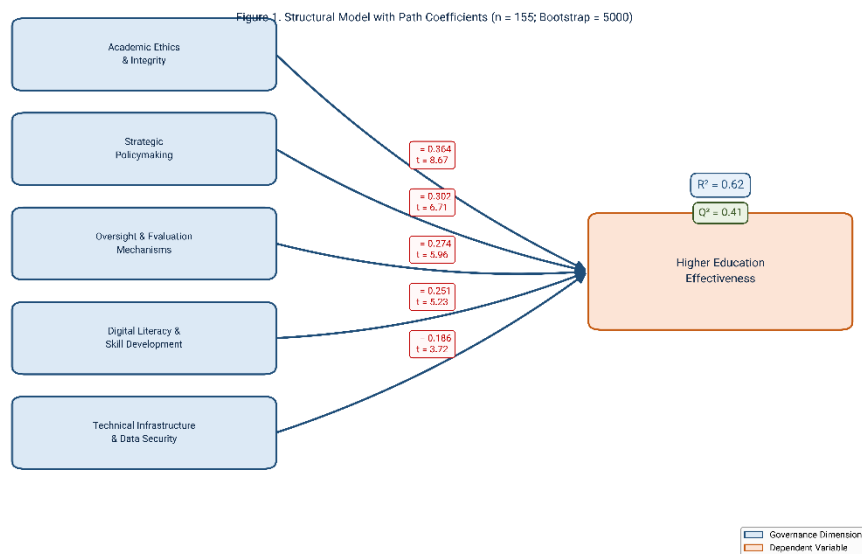
Index	Value	Threshold	Result
SRMR	0.062	< 0.08	Good fit
NFI	0.912	> 0.90	Good fit
R ²	0.62	> 0.50	Strong explanatory power

Q^2	0.41	> 0	Predictive power confirmed
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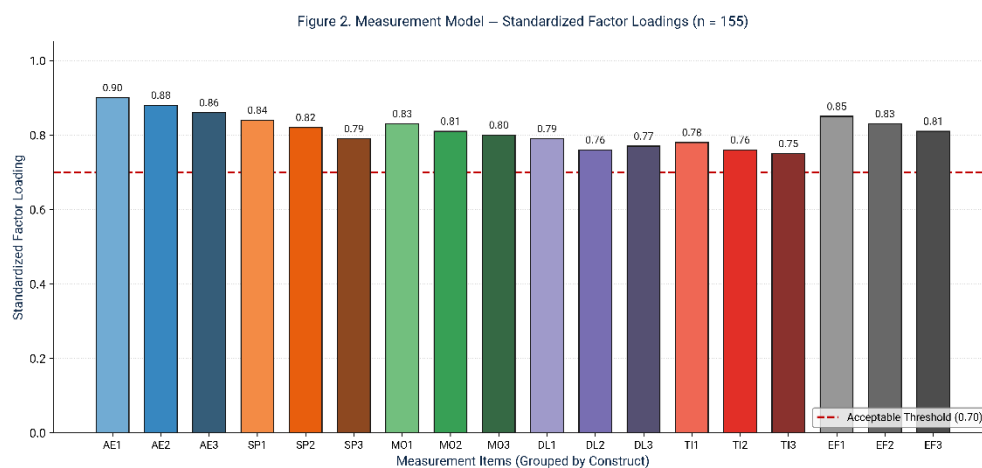
Table 11: Direct Effects and Ranking (n = 155)

Independent Variable	Direct Effect (β)	f^2	Rank
Academic Ethics and Integrity	0.364	0.17	1
Strategic Policymaking	0.302	0.11	2
Oversight and Evaluation Mechanisms	0.274	0.09	3
Digital Literacy and Skill Development	0.251	0.08	4
Technical Infrastructure and Security	0.186	0.05	5

A note on indirect effects. The conceptual model has no mediating variables. All five dimensions connect directly to the dependent variable. There are no indirect effects to report.

**Figure 1: Structural Model Path Coefficients**

Academic ethics had the largest direct effect ($\beta = 0.364$). Strategic policymaking came second (0.302), followed by oversight mechanisms (0.274), digital literacy (0.251), and technical infrastructure (0.186).

**Figure 2: Measurement Model — Standardized Factor Loadings**

All factor loadings exceeded 0.70. All t-values exceeded 1.96, confirming significance at the 95% level.

PLS-MGA was run in SmartPLS to test group differences.

Table 12: PLS-MGA Results

Dimension	Public (n=63)	Azad (n=55)	Non-Profit (n=37)	p (Pub vs Azad)	p (Pub vs Non-Profit)	Result
Academic Ethics	4.10	4.05	3.98	0.45	0.38	Not significant
Digital Literacy	3.65	3.75	3.58	0.31	0.52	Not significant
Strategic Policymaking	3.90	3.70	3.52	0.12	0.04	Significant for non-profit
Oversight Mechanisms	3.85	3.72	3.58	0.22	0.09	Not significant
Technical Infrastructure	3.55	3.40	2.95	0.18	< 0.001	Significant for non-profit

Two findings stand out. First, technical infrastructure differs significantly between public and non-profit universities ($p < 0.001$). Non-profit institutions score 2.95 on average—well below public universities (3.55) and Azad universities (3.40). Second, strategic policymaking differs between public universities and non-profit institutions ($p = 0.04$). Other dimensions show no significant group differences.

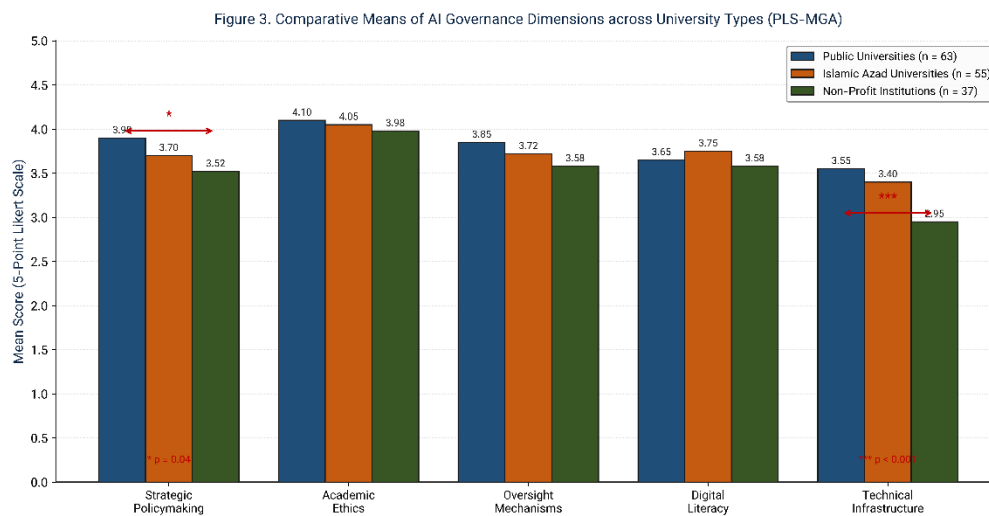


Figure 3: Comparative Means of AI Governance Dimensions

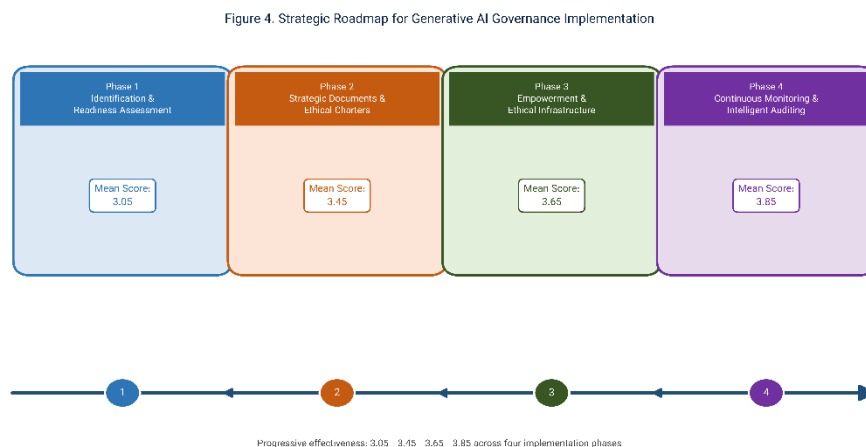


Figure 4: Effectiveness Trend Across Implementation Phases

The roadmap has four phases: identification and readiness assessment; drafting strategic documents and revising bylaws; empowerment and ethical infrastructure; and continuous monitoring with intelligent auditing. Scores climb from 3.05 in the pilot phase to 3.85 in the final evaluation—evidence of gradual organizational maturity.

Discussion and Conclusion

The present study developed and empirically validated a multidimensional governance model for generative artificial intelligence in higher education and scientific research. The findings showed that five dimensions—academic ethics and integrity, strategic policymaking, oversight and evaluation mechanisms, digital literacy and skill development, and technical infrastructure and data security—exerted positive and statistically significant effects on higher education effectiveness. The structural model demonstrated substantial explanatory and predictive capacity, with $(R^2 = 0.62)$ and $(Q^2 = 0.41)$, while SRMR = 0.062 and NFI = 0.912 indicated satisfactory overall model fit. Among the five dimensions, academic ethics and integrity had the strongest effect on higher education effectiveness ($\beta = 0.364$, $f^2 = 0.17$), followed by strategic policymaking ($\beta = 0.302$, $f^2 = 0.11$), oversight and evaluation mechanisms ($\beta = 0.274$, $f^2 = 0.09$), digital literacy and skill development ($\beta = 0.251$, $f^2 = 0.08$), and technical infrastructure and security ($\beta = 0.186$, $f^2 = 0.05$). These findings support the central premise that governance of generative AI cannot be reduced to a single policy or technological intervention. Instead, effective governance depends on a coordinated architecture in which normative, regulatory, supervisory, educational, and technological mechanisms function together. This interpretation is consistent with the broader literature demonstrating that generative AI simultaneously affects teaching, research, assessment, academic integrity, data governance, and institutional decision-making (9, 23). It also corresponds with the argument of Chiu that higher education institutions require systematic institutional transformation rather than isolated responses to GenAI (7). The magnitude of the explained variance further suggests that governance mechanisms constitute substantive determinants of institutional effectiveness in an AI-mediated academic environment rather than peripheral administrative considerations.

The strongest finding concerned academic ethics and integrity. Academic ethics achieved both the highest qualitative frequency and the strongest quantitative path coefficient, indicating that participants regarded ethical credibility as the central requirement for effective GenAI governance. This result can be interpreted in light of the distinctive challenge generative AI poses to conventional concepts of authorship, originality, plagiarism, accountability, and intellectual contribution. Traditional plagiarism typically involves identifiable textual appropriation, whereas generative systems can produce novel linguistic formulations that nevertheless represent substantial outsourcing of intellectual labor. Consequently, the issue is no longer merely whether text has been copied, but whether the submitted academic product authentically represents the student's or researcher's intellectual contribution. Perkins similarly argues that large language models compel universities to reconsider established academic integrity frameworks because conventional definitions of misconduct may be insufficient for AI-assisted academic production (13). Cotton and colleagues likewise emphasize that ChatGPT has disrupted conventional assumptions about cheating and requires institutions to combine policy reform with assessment redesign and clearer expectations regarding acceptable AI use (12). Sullivan and colleagues further maintain that responses to generative AI should simultaneously protect academic integrity and preserve meaningful learning rather than relying exclusively on detection or prohibition (15). The present result therefore suggests that ethics should not be interpreted as an obstacle to technological innovation. Rather, ethical clarity appears to create the legitimacy necessary for sustained adoption. When students, faculty members, and researchers understand what uses are permissible, what must be disclosed, and who remains accountable for generated content, technological adoption becomes more transparent and institutionally defensible.

The importance of academic integrity also aligns with emerging concerns regarding the reliability and authenticity of scientific communication. Gao and colleagues demonstrated that AI-generated scientific abstracts may be sufficiently convincing that human reviewers have difficulty distinguishing them from authentic abstracts, illustrating the limitations of relying on linguistic appearance as an indicator of genuine scholarship (10). Stokel-Walker and Van Noorden similarly

highlighted significant implications of ChatGPT and generative AI for scientific authorship, scholarly communication, and accountability (11). Williams emphasizes that the ethical implications of generative chatbots extend to transparency, intellectual ownership, fairness, privacy, and responsibility for machine-generated content (16). The present finding therefore reinforces the need to redefine academic integrity for an environment characterized by human–AI co-production. Such redefinition should move beyond the narrow question of whether AI has been used and instead evaluate the nature, extent, transparency, and educational legitimacy of that use. Luo's analysis of GenAI policies similarly questions traditional assumptions about the “originality” of student work and argues that institutional policies need to distinguish legitimate technological assistance from forms of substitution that undermine assessment validity (25). Thus, the strong contribution of academic ethics in the present model may reflect the fact that the legitimacy of all other GenAI applications ultimately depends on whether institutional stakeholders trust that academic standards remain meaningful.

Strategic policymaking emerged as the second strongest predictor of higher education effectiveness. This finding demonstrates that responsible GenAI adoption requires explicit institutional direction rather than informal adaptation by individual faculty members or students. Policies are particularly important because ambiguity concerning acceptable use can produce inconsistent practices across faculties, courses, research groups, and institutions. Wang and colleagues found considerable variation among university policies, resources, and guidelines concerning ChatGPT and related technologies, indicating that institutional responses differ substantially in both scope and maturity (24). Orfanidis similarly identified substantial moral diversity across institutional policies governing student use of generative AI, demonstrating that universities differ not only in regulatory strictness but also in their underlying conceptions of responsibility, autonomy, fairness, and academic values (26). The positive relationship identified in the present study suggests that policy clarity enhances effectiveness by reducing uncertainty and establishing shared expectations regarding disclosure, assessment, data use, research practices, and accountability. Jiang and colleagues likewise emphasize that effective institutional GenAI policies require more than formal existence; regulations must be sufficiently clear, legitimate, implementable, and responsive to the needs of stakeholders (27). Accordingly, strategic policymaking should be conceived as an adaptive governance function through which universities continuously translate broad ethical principles into operational rules.

The significance of strategic policymaking can also be explained through the rapid pace of technological development. Generative models evolve considerably faster than traditional university regulations, creating the risk that fixed institutional policies will rapidly become outdated. Farrokhnia and colleagues describe generative AI as presenting simultaneous strengths, weaknesses, opportunities, and threats, implying that institutional strategies must remain flexible and regularly updated as technological capabilities and risks change (22). Rahman and Watanobe similarly argue that universities should adopt strategic approaches capable of balancing the opportunities of ChatGPT with threats involving misinformation, dependency, integrity, and misuse (21). At the national level, the present finding is compatible with Farajzadeh's emphasis on the necessity of macro-level science and technology policies for governing emerging technologies (30). It is also consistent with Salimi's argument that university governance structures require revision in response to rapidly developing technologies (29). The findings consequently imply that institutional policy should not consist of a single prohibition or permission statement. Rather, universities need differentiated policies specifying permissible uses across educational levels, research activities, assessments, thesis preparation, data analysis, publication, and administrative functions, with mechanisms for periodic revision.

Oversight and evaluation mechanisms constituted the third strongest predictor of effectiveness. This finding indicates that ethical principles and written policies must be accompanied by monitoring and evaluative capacities if they are to shape actual behavior. Governance without oversight may produce symbolic compliance in which institutions publish guidelines but lack the organizational capacity to assess implementation. The result supports the argument that conventional supervisory systems

are insufficient for technologies whose outputs may be difficult to detect and whose capabilities change rapidly. Cotton and colleagues note that AI-generated content poses significant challenges to conventional academic misconduct detection, requiring institutions to reconsider how integrity is monitored (12). Rudolph and colleagues similarly question the continuing viability of some traditional assessment formats when conversational AI can produce sophisticated responses with minimal student involvement (14). The present findings suggest that effective oversight should therefore combine technological, procedural, and human mechanisms. Pure dependence on automated AI detectors would be problematic because detection systems may generate false positives or become less effective as models evolve. A more defensible model involves process-oriented assessment, documentation of AI assistance, oral verification when necessary, expert review, and periodic institutional audits. Such an approach corresponds with the UNESCO emphasis on maintaining meaningful human oversight and accountability in educational applications of generative AI (23).

Digital literacy and skill development also showed a significant positive relationship with higher education effectiveness. The finding indicates that regulation by itself is inadequate if users lack the competence to understand and responsibly employ AI systems. Digital literacy in the generative AI era extends beyond conventional familiarity with software. It includes an understanding of model limitations, effective interaction with AI systems, critical evaluation of outputs, recognition of bias and hallucination, verification of claims, ethical awareness, and the capacity to decide when AI assistance is appropriate. Naamati-Schneider and Alt describe this development as a transition beyond conventional digital literacy toward new competencies required for interaction with AI-powered assistants (6). Grassini similarly emphasizes that AI can improve educational processes but can also undermine critical thinking and meaningful learning when students become cognitively dependent on automated outputs (20). The current result therefore indicates that AI literacy should be understood as a protective as well as an enabling capacity. Users with stronger AI literacy are more capable of exploiting technological benefits while recognizing inaccuracies, limitations, and ethical risks.

The importance of literacy is also consistent with findings from educational applications of AI. Guan and colleagues found that AI-supported informal digital English learning can positively affect proficiency, motivation, and self-regulation, but such benefits depend on how learners engage with technology (5). Salas-Pilco and Yang likewise demonstrate that the effectiveness of AI applications in higher education is shaped by institutional context, user capacity, and implementation conditions (28). Lo's rapid review indicates that ChatGPT can support learning through personalized assistance, explanation, and feedback while simultaneously producing challenges related to accuracy, assessment, and dependency (3). Opara and colleagues similarly describe a balance between educational opportunities and risks arising from uncritical or inappropriate use (19). These studies support the present conclusion that universities should not assume that access to generative AI automatically produces educational benefit. Educational value depends on whether students and faculty possess sufficient competence to interrogate outputs, verify evidence, preserve intellectual independence, and integrate AI assistance into authentic disciplinary reasoning.

Technical infrastructure and data security demonstrated the smallest direct effect, although its relationship with higher education effectiveness remained statistically significant. This finding should not be interpreted as indicating that infrastructure is unimportant. Rather, its role may be foundational: infrastructure enables the implementation of policies, literacy initiatives, oversight systems, and secure applications even when its direct statistical contribution is comparatively smaller. Concerns regarding data privacy are especially relevant because externally hosted generative AI platforms may process academic, personal, administrative, or unpublished research information beyond direct institutional control. Lund and Wang identify important implications of ChatGPT for academic information environments and libraries, including questions of reliability, data handling, and institutional adaptation (8). Williams likewise emphasizes privacy and accountability as major ethical issues in higher education adoption of generative chatbots (16). Technical governance should therefore involve approved-platform

policies, data classification, authentication, secure institutional environments, procurement standards, and restrictions on uploading confidential or identifiable information to external systems.

The multi-group analysis further enriched this interpretation by demonstrating significant institutional differences. Technical infrastructure differed significantly between public and non-profit universities, with non-profit institutions reporting substantially lower levels, while strategic policymaking also differed significantly between public and non-profit institutions. In contrast, academic ethics, digital literacy, and oversight mechanisms did not significantly differ across institution types. This pattern suggests that certain AI governance challenges are universal, whereas others are sensitive to organizational resources and institutional structure. The absence of significant differences in ethics and literacy implies that concerns about responsible AI use extend broadly across higher education regardless of ownership type. By contrast, infrastructure is strongly conditioned by financial capacity, access to technology, and administrative investment. This interpretation is consistent with Williamson and Eynon's argument that AI in education must be understood within broader social and institutional structures rather than as a technologically neutral innovation (1). Baker and colleagues likewise emphasize that visions of AI in education are connected to broader assumptions concerning intelligence, humanity, and institutional futures (2). Consequently, policies based on identical implementation expectations across all institutions may inadvertently widen existing inequalities. Governance frameworks should establish common ethical and regulatory standards while providing differentiated technical and financial support according to institutional capacity.

Taken together, the findings support a conception of generative AI governance as an integrated institutional ecosystem. Ethical integrity establishes normative legitimacy; strategic policymaking translates values into rules; oversight ensures implementation and accountability; digital literacy develops the human capabilities necessary for responsible interaction; and technical infrastructure provides the secure environment within which these processes can operate. This interpretation is compatible with Tlili's characterization of educational chatbots as technologies whose positive or negative effects depend fundamentally on the conditions of implementation (18). It also corresponds with Chiu's call for research and institutional development that treats generative AI transformation as a systemic higher education issue (7). The model therefore moves beyond both technological determinism and prohibition-oriented governance. Neither unrestricted adoption nor complete exclusion adequately addresses the complexity of generative AI. Effective governance instead requires universities to institutionalize responsible experimentation within clear ethical boundaries, continuously revise policies as technologies develop, strengthen human capabilities, monitor implementation, and maintain control over sensitive academic data.

The present study has several limitations that should be considered when interpreting its findings. First, although the quantitative sample of 155 faculty members and researchers was adequate for PLS-SEM estimation and produced stable measurement and structural model results, the sample remains relatively limited for broad generalization across the highly heterogeneous higher education sector. Differences among disciplines, geographical regions, institutional sizes, research intensity, academic ranks, and levels of technological maturity may therefore not have been fully captured. Second, the qualitative phase included ten experts. Although participants represented technical, legal, ethical, educational, and managerial backgrounds and thematic saturation was achieved, a larger and more geographically diverse expert panel might have identified additional governance dimensions or more nuanced subdimensions. Third, the cross-sectional nature of the quantitative phase means that the identified relationships represent associations observed at a particular stage of generative AI development and cannot establish long-term causal effects. Fourth, the model examined direct relationships between the five governance dimensions and higher education effectiveness and did not include mediating or moderating mechanisms. Finally, generative AI is evolving unusually rapidly; consequently, specific governance challenges, technological capabilities, security risks, and

institutional practices may change faster than is typical in higher education research, potentially limiting the temporal stability of some findings.

Future studies should validate the proposed model using larger samples drawn from multiple regions, academic disciplines, university types, and national higher education systems to examine its external validity and cross-cultural applicability. Longitudinal research would be particularly valuable because it could determine how governance maturity, institutional effectiveness, user competence, and attitudes toward AI evolve as policies and technologies change. Researchers should also examine mediation and moderation mechanisms, such as whether strategic policymaking improves effectiveness partly through enhanced digital literacy, stronger oversight, or improved infrastructure, and whether organizational culture, institutional resources, academic discipline, or technology readiness moderate these relationships. Multi-group analyses could be expanded to compare public, private, non-profit, research-intensive, teaching-oriented, and technology-focused institutions. Future studies could also apply complementary approaches such as Interpretive Structural Modeling, MICMAC analysis, DEMATEL, system dynamics, or longitudinal structural equation modeling to identify hierarchical and reciprocal relationships among governance components. Additional qualitative research should investigate the experiences of students, administrators, research ethics committees, IT personnel, librarians, journal editors, and policymakers, while future models should consider emerging issues such as autonomous AI agents, multimodal systems, locally hosted language models, AI-generated research data, and potential developments toward more general-purpose artificial intelligence.

Higher education policymakers and university administrators should translate the five validated governance dimensions into an integrated institutional implementation framework rather than addressing each dimension independently. Universities should formulate explicit and regularly updated AI policies that distinguish acceptable, conditionally acceptable, and prohibited uses across coursework, examinations, theses, research, publication, peer review, data analysis, and administrative activities. Academic integrity regulations should require transparent disclosure of substantive AI assistance while avoiding exclusive reliance on automated detection systems. Interdisciplinary AI governance committees should be established with representation from academic leadership, ethics committees, legal specialists, educational experts, IT professionals, faculty members, and students. Institutions should implement continuous AI literacy programs tailored to different disciplinary and professional needs, with training extending beyond prompt engineering to output verification, bias awareness, privacy protection, responsible citation, and preservation of independent reasoning. Universities should also classify sensitive data, establish rules concerning information that may not be entered into commercial AI systems, assess platforms before institutional adoption, and progressively develop secure local or institutionally controlled AI environments. Finally, because the findings indicate disparities in technical infrastructure and strategic policymaking across university types, national authorities should provide targeted financial, technical, and regulatory support to institutions with weaker technological capacity so that responsible GenAI adoption does not intensify existing inequalities within the higher education system.

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All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adhered in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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