International Research Journal of Multidisciplinary Scope (IRJMS), 2026;7(3):1154-1167

Original Article | ISSN (O): 2582-631X DOI:10.47857/irjms.2026.v07i03.011001

A Governance Framework for Responsible AI Integration in Higher Education: A Fuzzy Delphi Study

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Abstract

The rapid integration of artificial intelligence (AI) in higher education presents both transformative opportunities and major governance challenges. Many institutions still lack structured mechanisms to ensure responsible and coordinated implementation. This study identifies and prioritizes key design principles for institution-wide AI integration in Malaysian higher education through the Fuzzy Delphi Method (FDM). A panel of twelve experts assessed proposed principles organized across five socio-technical domains: Governance and Strategy, Technology and Infrastructure, Data and Analytics, Ethics, Risk and Compliance and Change Management and Workforce Enablement. Consensus was established using a threshold value of d ≤ 0.2 with a minimum agreement rate of 75%. All five domains achieved consensus, with Governance and Strategy emerging as the highest priority, followed by Data and Analytics, Ethics, Risk and Compliance, Technology and Infrastructure and Change Management and Workforce Enablement. These findings suggest that sustainable AI adoption requires institutions to first establish robust governance structures, ensure data readiness and embed ethical safeguards before expanding technological investments. This study contributes a validated, prioritized socio-technical framework offering evidence-based guidance for university leaders, with particular relevance for resource-constrained higher education contexts in Malaysia and the broader Global South.

Keywords: Artificial Intelligence Governance, Fuzzy Delphi Method, Higher Education Institutions, Responsible AI Integration, Socio-technical Systems Framework.

Introduction

The integration of artificial intelligence (AI) into higher education has moved rapidly from isolated pilots to enterprise-scale deployment, reshaping how universities deliver student services, administer research, allocate resources and generate institutional intelligence (1, 2). Functions that once depended on human judgment are increasingly mediated by AI-driven systems (3). Early implementations have demonstrated efficiency gains and decision-support improvements, creating institutional momentum. However, the transition from promising pilot to responsible, institution-wide integration remains rare (4, 5), with adoption typically fragmented and tool-driven, lacking the governance structures, data foundations, ethical safeguards and change management capabilities required for coherent, accountable outcomes (6, 7). A conceptual distinction is necessary between the operational use of AI, that is, the deployment of individual AI tools within specific departments such as a chatbot for student enquiries or a predictive-analytics dashboard in admissions and enterprise-level AI governance, which refers to institution-wide strategic coordination encompassing unified policy frameworks, centralized oversight bodies, cross-functional risk management and systematic workforce enablement. This study addresses the latter, because the challenges universities face in scaling AI are overwhelmingly governance challenges of coordination, accountability, data integration and workforce readiness that cannot be resolved at the level of individual tool deployments. Universities that pursue AI adoption without coordinated institutional strategy risk accumulating disparate point solutions that create technical debt, amplify risk and fail to deliver strategic value (8). These challenges are particularly acute in the Global South, including Malaysia, where higher education systems face ambitious digitalization mandates alongside structural constraints in funding, infrastructure,

(Received 06th March 2026; Accepted 17th June 2026; Published 18th July 2026)

and capacity (9, 10). Decisions mediated by AI systems, ranging from student progression analytics and financial-aid eligibility scoring to admissions screening and automated academic-integrity detection, directly shape student outcomes, institutional reputation and the equitable distribution of educational opportunity. When these systems are deployed without coherent governance, universities may inadvertently encode bias, erode procedural fairness, or expose themselves to regulatory non-compliance and reputational damage. Malaysian higher education provides a particularly illustrative case: the sector has been positioned by national policy as central to the country's digital-economy aspirations, yet the pace of institutional AI adoption has outstripped the maturity of the governance, data and ethical frameworks needed to support it responsibly.

The scholarly literature has not yet adequately addressed this governance challenge. Existing studies predominantly focus on Global North contexts, course-level applications, or technology-centric deployment roadmaps that treat governance and ethics as secondary considerations (11–14). No validated, prioritized framework integrates these concerns into a sequenced guide sensitive to resource-constrained environments (15). Frameworks developed in well-resourced Western contexts often presuppose governance maturity, regulatory clarity and workforce digital readiness that cannot be assumed in Global South settings and the prevailing tool-centric guidance leaves institutional leaders without a defensible basis for sequencing investments, allocating scarce resources, or justifying the deferral of attractive but premature technology deployments. Closing this gap requires not only identifying which domains matter but establishing, on the basis of structured expert input, how they should be prioritized in practice.

Grounded in Socio-Technical Systems (STS) theory, this study applies the Fuzzy Delphi Method (FDM) to capture expert consensus on design principles for institution-wide AI integration in Malaysian higher education. STS theory posits that sustainable organizational performance requires joint optimization of social and technical subsystems (16, 17). The FDM was selected because it aggregates expert judgement under conditions of conceptual ambiguity and converts linguistic ratings into fuzzy numbers, producing transparent and replicable consensus and prioritization measures (18, 19). Two research questions guide the study: RQ [1]. What design principles are considered essential for responsible, institution-wide AI integration in higher education? RQ 2. How should these principles be prioritized to guide sequencing, resourcing and risk management during implementation? The study makes four contributions: a consolidated socio-technical framework spanning university enterprise architecture; FDM-based empirical validation and prioritization; sequenced implementation guidance for portfolio planning; and contextualization within the Malaysian and Global South research gap.

STS theory warns against technology-led change that prioritizes tool deployment without redesigning the human work systems that use them (20-22). This study operationalizes STS theory across five interdependent domains: Governance and Strategy (D1), Technology and Infrastructure (D2), Data and Analytics (D3), Ethics, Risk and Compliance (D4) and Change Management and Workforce Enablement (D5). The five domains map onto STS subsystems and the priority ranking reported in the findings reflects the sequence in which each subsystem must be stabilized for joint optimization to be sustained.

Effective AI governance in universities requires strategic alignment, clear accountability structures and portfolio management mechanisms (23-32). Universities are pluralistic organizations in which academic autonomy, administrative authority and student welfare obligations coexist, so governance must extend beyond conventional IT steering committees to include academic leadership, legal counsel, data stewards, ethics representatives and student-affairs voices in cross-functional oversight structures. The OECD AI Principles and the UNESCO Recommendation on the Ethics of AI provide normative anchors that treat governance not as a supplementary safeguard but as a constitutive element of legitimate AI use (33, 34). Strategic alignment is equally important: AI investments that are disconnected from institutional strategy tend to produce isolated tools that solve narrow problems while creating new integration, maintenance and risk burdens at the enterprise level and portfolio management mechanisms such as stage-gate review processes and value-realization tracking allow institutions to maintain visibility over the cumulative effect of multiple AI initiatives.

Technology infrastructure and data readiness constitute the technical prerequisites for reliable AI. Enterprise-grade AI requires secure and interoperable platforms, centralized identity and access management, resilience planning and access equity (35-39). Data readiness requires catalogs, lineage documentation, quality service-level agreements, continuous monitoring for drift and bias and explainability documentation, including model cards and decision logs that provide the transparency artefacts allowing institutional users and external stakeholders to understand and contest AI-mediated decisions (40-44).

A persistent gap exists between ethical principal articulation and institutional operationalization. Global frameworks converge on fairness, transparency, accountability, human oversight and privacy protection, yet these have been shown to remain aspirational in most institutions (45-49). Operationalization requires privacy-by-design protocols, pre-deployment bias assessments, transparent user disclosure, formal incident response procedures and Value-Sensitive Design methodologies (50-52).

Technology transformations have been shown to fail without sustained attention to vision clarity, stakeholder engagement and workforce capability development (53-55). Role-based training programmes, AI champion networks, strategic communications and systematic adoption tracking are considered essential (56, 57). Workforce enablement must be understood as an ongoing commitment rather than a pre-launch activity, evolving alongside the institutional AI portfolio.

Malaysia presents a particularly instructive case study. The Malaysia Education Blueprint 2015-2025 and the MyDIGITAL initiative position AI adoption as a strategic priority (58-60). However, this national ambition operates alongside constraints characteristic of many Global South contexts: uneven data infrastructure maturity, fragmented capacity-building, budgetary pressures and a complex regulatory landscape. The Personal Data Protection Act pre-dates the current AI landscape and the Malaysian Qualifications Agency has only recently begun incorporating digital-readiness criteria into accreditation reviews. Dominant frameworks developed in well-resourced Western settings assume governance maturity, regulatory clarity and workforce digital readiness that cannot be presupposed in Malaysian higher education, making prioritization research particularly urgent in this context.

This study proposes a framework grounded in STS theory, structured across five interdependent domains coordinated by Governance and Strategy at the centre, with bidirectional links between the technical and social subsystems (61-65). The structure and interactions are illustrated in Figure 1.

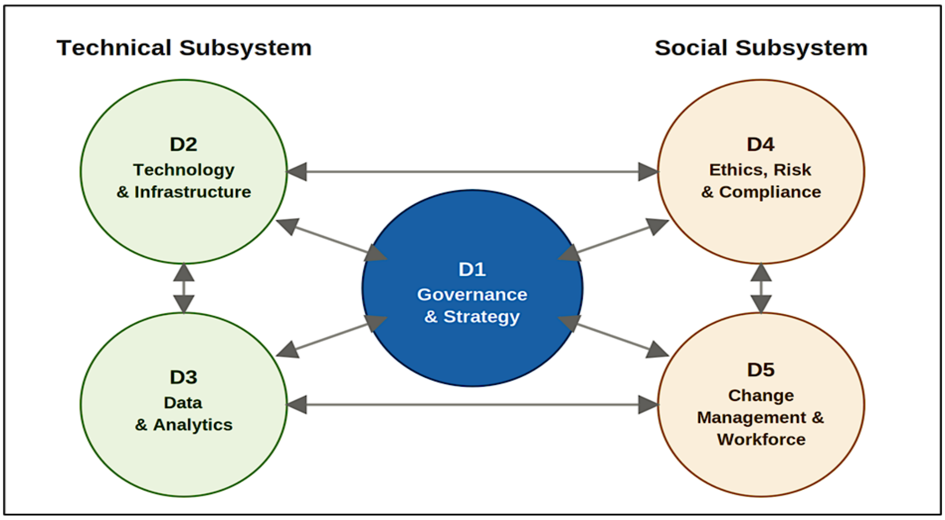

Figure 1: Socio-technical Framework for AI Integration in Higher Education based on STS theory (16)

As illustrated in Figure 1, the framework arranges five interdependent domains around Governance and Strategy (D1) at the centre, distinguishing a Technical Subsystem (D2 Technology and Infrastructure; D3 Data and Analytics) from a Social Subsystem (D4 Ethics, Risk and Compliance; D5 Change Management and Workforce Enablement). Bidirectional arrows indicate that joint optimisation between the technical and social subsystems is continuously coordinated through D1, rather than imposed in a top-down hierarchy. Cross-subsystem links between D2–D4 and D3–D5 further capture the interdependencies between infrastructure choices and ethical risk and between data maturity and workforce capability. The figure therefore presents the framework as a dynamic system in which any change in one domain propagates effects across the others.

Methodology

This study adopted a quantitative research design employing the Fuzzy Delphi Method (FDM) to establish expert consensus on design principles for responsible, institution-wide AI integration in higher education. The FDM was selected for its suitability to research contexts characterized by complexity and uncertainty (17, 66, 67).

The selection of FDM over other consensus-building methods followed a deliberate methodological comparison. The classical Delphi technique produces qualitative agreement rather than a quantitative consensus measure and is vulnerable to participant attrition across rounds. FDM retains structured-anonymity logic while resolving these limitations through conversion of linguistic judgements into triangular fuzzy numbers, yielding a mathematically auditable, single-round measure of both consensus [$d \leq 0.2$] and priority (via defuzzification). DEMATEL is informative for mapping causal dependencies but presupposes those elements have already been validated. ISM is suited to hierarchical structural modelling but does not produce the gradational, fuzzy-encoded endorsement measure required here. AHP imposes a heavy cognitive burden, exhibits sensitivity to rank-reversal and assumes crisp numerical precision poorly matched to AI governance uncertainty. FDM was therefore judged most defensible because it simultaneously accommodates linguistic uncertainty, produces both validation and prioritization in a single round and is established in higher-education policy research (17, 18, 67). DEMATEL and ISM are noted as productive complements for future causal-modelling work.

Expert Panel

A panel of twelve experts was purposively selected to represent the range of institutional functions implicated in enterprise AI integration. Panel size followed the criterion that ten to fifty experts are sufficient when high domain expertise can be expected (19).

The twelve panellists collectively averaged 16.8 years of professional experience (range: 10–28 years). Affiliations spanned seven Malaysian public and private universities, with all panellists serving as lecturers in roles directly relevant to AI integration. The study was coordinated from UNITAR International University, Petaling Jaya, Selangor, Malaysia (GPS coordinates: [3.1063] ° N, [101.6068] ° E), with panellists participating remotely from their respective institutions across Malaysia. Four inclusion criteria applied:

(i) doctoral qualification;
(ii) minimum ten years' experience in higher education, enterprise digital governance, or AI-related policy;
iii) current or recent role involving named responsibility for AI policy, data governance, or enterprise AI systems; and
iv) prior involvement in at least one institution-level AI or digital-transformation initiative.

Table 1 summarizes expert profiles while preserving confidentiality. Table 1 provides a profile of the twelve expert panellists who participated in the Fuzzy Delphi exercise, summarising their current roles, institutional category, years of professional experience and primary areas of AI-related expertise. The panel represents a deliberately balanced mix of lecturers from public-sector and private-sector universities across multiple disciplines, ensuring that the consensus reflects multiple vantage points on enterprise AI integration. Individual identities and institutional affiliations have been withheld in line with the confidentiality protocol described above.

Table 1: Expert Panel Profile (n = 12)

ID	Current Role	Institution	Years	AI Expertise
E [1]	Senior Lecturer, IT Governance	Public university	23	Enterprise AI strategy, IT governance
E [2]	Senior Lecturer, Digital Transformation	Public university	19	AI governance, portfolio management
E [3]	Senior Lecturer, Data Governance	Public university	16	Data governance, lineage, quality
E [4]	Associate Professor, Education Policy	Private university	28	Institutional strategy, AI policy
E [5]	Senior Lecturer, Learning Analytics	Private university	14	Learning analytics, AI in academics
E [6]	Senior Lecturer, Cybersecurity	Public university	17	AI risk, cybersecurity, compliance
E [7]	Senior Lecturer, AI Policy & Ethics	Public university	21	National AI policy, ethics regulation
E [8]	Associate Professor, Computing	Public university	20	Responsible AI, algorithmic accountability
E [9]	Senior Lecturer, Teaching Innovation	Private university	12	Generative AI, workforce enablement
E [10]	Senior Lecturer, Enterprise Systems	Private university	15	Enterprise AI infrastructure
E [11]	Senior Lecturer, Law & Data Protection	Public university	11	Data protection, AI ethics, compliance
E [12]	Senior Lecturer, Organisational Development	Private university	10	Change management, AI literacy

Note: Individual names and institutional affiliations withheld for confidentiality.

Linguistic Scale and Average Fuzzy Value

The five-point fuzzy linguistic scale used to capture expert ratings is shown in Table 2. Each linguistic variable, ranging from Strongly Disagree to Strongly Agree, is mapped to a triangular fuzzy number that encodes the lower bound, the most likely value and the upper bound of the underlying judgement. This conversion allows the linguistic ambiguity inherent in expert opinions to be aggregated and defuzzified mathematically. The same scale is applied uniformly to every item across the five socio-technical domains.

Table 2: Five-point Fuzzy Linguistic Scale

Linguistic Variable	Triangular Fuzzy Number
Strongly Disagree	[0.0, 0.0, 0.2]
Disagree	[0.0, 0.2, 0.4]
Moderately Agree	[0.2, 0.4, 0.6]
Agree	[0.4, 0.6, 0.8]
Strongly Agree	[0.6, 0.8, 1.0]

Threshold Value and Consensus

The threshold value (d) was computed for each expert-item pair. A criterion of $d \leq 0.2$ was applied for individual agreement, with consensus declared when at least 75% of experts met this limit (66).

The threshold of $d \leq 0.2$ was selected from established FDM literature and re-validated in educational research (18, 66, 67). A stricter value ($d \leq 0.1$) would over-penalise legitimate variation between experts from distinct roles, while a more permissive value ($d \leq 0.3$) would risk reporting superficial agreement as genuine consensus. The 75% panel-agreement minimum is more stringent than the 51% sometimes used in policy Delphi work (19). Two items fell close to the threshold: Expert E9 returned $d = 0.21$ on one item in Technology and Infrastructure (access equity for low-bandwidth contexts) and Expert E12 returned $d = 0.20$ on one item in Change Management (longitudinal competency tracking). The pre-specified handling protocol was applied: items were retained because overall domains still met the 75% minimum (both at 92%); divergent experts were contacted for clarifying consultation, confirming their residual disagreement concerned operational feasibility rather than the principle itself.

Instrument

Data were collected using a structured questionnaire organized into two sections. The second section presented candidate design principles under five socio-technical domains, each rated using the five-point fuzzy linguistic scale. Items were derived from the literature and refined through pilot interviews.

The pilot study involved three subject-matter specialists not on the main panel: one senior university IT director, one institutional-research officer with learning analytics experience and one academic with published research in AI ethics in education. Each specialist reviewed the draft instrument against three criteria:

(i) clarity of item wording,
(ii) professional relevance and
iii) domain placement.

The pilot resulted in three changes: two items in Ethics, Risk and Compliance were re-worded (one to sharpen the distinction between privacy-by-design and general data-protection compliance, the other to introduce an explicit trade-off between algorithmic transparency and institutional confidentiality) and one item originally in Technology and Infrastructure (data-quality SLAs) was reassigned to Data and Analytics. No items were added or removed. Pilot data did not enter the main FDM analysis; the pilot served exclusively as content validation.

Procedure

The procedural steps followed in applying the Fuzzy Delphi Method are summarised in Table 3. The six steps move sequentially from the purposive selection of the expert panel and definition of the fuzzy linguistic scale, through the computation of average fuzzy values and the application of the threshold criterion, to the fuzzy evaluation of each domain and the final defuzzification into a crisp priority ranking. This sequence ensures that both consensus validation and prioritisation are produced within a single, mathematically auditable round.

Table 3: Summary of FDM Procedural Steps

Step	Procedure	Purpose
Step 1	Determine expert panel	Purposive selection of 12 domain experts
Step 2	Define linguistic scale	Five-point fuzzy scale at Table 2
Step 3	Compute average fuzzy values	Aggregate expert responses per item
Step 4	Determine threshold (d)	d ≤ 0.2; ≥75% agreement required
Step 5	Fuzzy evaluation	Compute domain-level fuzzy scores
Step 6	Defuzzification	Convert fuzzy scores to crisp priority ranking

The study was administered in a single round. All five domains achieved consensus in the first round, making a second round unnecessary.

Participants

Table 4 shows the distribution of the twelve panellists across functional categories within the higher-education and AI-policy ecosystem. The panel includes three lecturers in academic leadership roles, three lecturers in IT and enterprise systems, two lecturers in data governance, two lecturers in teaching and analytics and two lecturers in law and policy. This functional spread was designed to ensure that the consensus reflects the full range of decision-makers implicated in institution-wide AI governance, rather than the perspective of any single professional community.

Table 4: Distribution of Expert Panel by Category

Category	Roles	n
Academic Leadership	Senior Lecturers, Academic Leadership	3
IT & Enterprise Systems	Senior Lecturers, IT & Enterprise Systems	2
Data Governance	Senior Lecturers, Data Governance	2
Teaching & Analytics	Senior Lecturers, Teaching & Analytics	2
Law & Policy	Senior Lecturers, Law & Policy	2
Total		12

Note: n= Number of Respondents.

Results and Discussion

Findings

All five socio-technical domains achieved expert consensus, confirming their essential role in responsible AI integration (RQ1). The defuzzification results establish a priority ranking (RQ2): Governance and Strategy [0.85], Data and Analytics [0.83], Ethics, Risk and Compliance [0.82], Technology and Infrastructure [0.80] and Change Management and Workforce Enablement [0.79].

Table 5 reports the defuzzified scores, average threshold (d) values and panel agreement percentages for each of the five socio-technical domains. All five domains satisfied the dual consensus criteria of $d \leq 0.2$ and a minimum agreement rate of 75% and were therefore accepted as essential to responsible, institution-wide AI integration. The defuzzified scores range from [0.79] to [0.85], with average d values clustering between [0.12] and [0.15], indicating tight convergence across the panel. These results address RQ 1 by confirming the validity of the proposed framework.

Table 5: Fuzzy Delphi Consensus Results by Domain

Domain	Defuzz.	Avg d	Agreement	Status
D [1]: Governance & Strategy	[0.85]	[0.12]	[92%]	Accept
D [2]: Technology & Infrastructure	[0.80]	[0.14]	[92%]	Accept
D [3]: Data & Analytics	[0.83]	[0.13]	[92%]	Accept
D [4]: Ethics, Risk & Compliance	[0.82]	[0.15]	[83%]	Accept
D [5]: Change Mgmt & Workforce	[0.79]	[0.14]	[92%]	Accept

The resulting priority ranking across the five socio-technical domains is presented in Table 6, ordering them from highest to lowest defuzzified score. Governance and Strategy occupies the highest priority position, followed by Data and Analytics, Ethics, Risk and Compliance, Technology and Infrastructure and Change Management and Workforce Enablement. This ranking addresses RQ2 by providing institutions with an empirically grounded sequence for resourcing and risk management during AI integration. The implications of this sequencing are discussed in the subsections that follow.

Table 6: Domain Priority Ranking

Rank	Domain	Score	Priority
[1]	Governance and Strategy	[0.85]	Highest
[2]	Data and Analytics	[0.83]	High
[3]	Ethics, Risk and Compliance	[0.82]	High
[4]	Technology and Infrastructure	[0.80]	Moderate–High
[5]	Change Mgmt and Workforce Enablement	[0.79]	Moderate–High

The Primacy of Governance and Strategy

Governance and Strategy [0.85] confirms that technology initiatives fail not primarily because of technological shortcomings but because of insufficient governance, unclear leadership and weakly defined decision rights (24, 30, 68, 69). The panel's placement of this domain at the top of the priority ranking reflects a broader recognition in the IT governance literature that strategic alignment and accountability structures are the most consequential determinants of digital-transformation success. For Malaysian and Global South institutions, this prioritization carries direct practical significance: governance structures must be established before technological investments are scaled (33, 34, 70, 71). Without such structures, universities risk repeating the pattern of disparate point solutions, technical debt and fragmented accountability that has characterized earlier waves of digital adoption (8).

This finding aligns with established research showing that governance maturity is the single strongest predictor of whether enterprise technology investments deliver intended strategic value (24, 68, 69). It also resonates with the STS principle of joint optimization: governance is the institutional mechanism through which social and technical subsystems are deliberately co-designed, ensuring that AI tools are introduced alongside the decision-rights frameworks, accountability protocols and oversight bodies that make their use defensible (16, 20). In the Malaysian context, where the Personal Data Protection Act [2010] pre-dates current AI capabilities and the Malaysian Qualifications Agency has only recently begun incorporating digital-readiness criteria into accreditation reviews, the absence of mature AI governance leaves universities exposed to compliance ambiguity and reputational risk (33, 34). The panel's emphasis on governance therefore should not be interpreted as an abstract preference for structure; rather, it reflects a pragmatic recognition that AI integration in resource-constrained environments cannot succeed without first clarifying who decides, who is accountable and how decisions are reviewed.

Data and Analytics as a Strategic Prerequisite

Data and Analytics [0.83] reflects the dependence of AI system reliability on data quality, governance and transparency (35, 41, 42). The panel's elevation of this domain above Technology and Infrastructure is itself an important finding: it indicates that experts recognize data as a strategic asset rather than a by-product of digital operations. AI systems trained on incomplete, inconsistent, or biased data produce outputs that are not only inaccurate but also institutionally consequential, particularly in high-stakes contexts such as student progression decisions, financial-aid allocation and admissions screening (40, 47). Explainability documentation, including model cards and audit trails, connects this domain to user trust and aligns with global XAI research showing that transparency about training data and model logic is a precondition for legitimate algorithmic authority (44, 72).

For Malaysian institutions, where legacy systems and heterogeneous data environments are common, this elevates data governance to a strategic priority (3, 8). Many universities still operate fragmented student information systems, learning management platforms and finance databases that were never designed to exchange data in real time, creating significant barriers to enterprise AI deployment (36, 64, 65). The implication is that data readiness must be addressed before, not in parallel with, large-scale AI investment. Operationally, this requires institutions to establish data catalogues, enforce contractual data-quality standards with third-party providers, implement formalized data-lineage tracking and develop continuous monitoring protocols for drift and bias (41, 42, 63). These activities are neither glamorous nor visible to external stakeholders, yet the present findings suggest that they constitute the foundation on which all subsequent AI capability rests.

Ethics, Risk and Compliance as an Operational Imperative

Ethics, Risk and Compliance [0.82] confirms ethical governance as an operational requirement rather than an aspirational ideal. The expert mandate for pre-deployment privacy impact assessments and bias audits operationalizes global policy convergence around fairness, accountability, transparency, privacy and human oversight (33, 34, 45, 46, 50). The high priority assigned to this domain echoes a broader concern in the AI ethics literature: that institutional commitment to ethical principles often remains rhetorical, with universities articulating values without establishing the mechanisms through which those values become enforceable (45, 46). The present findings suggest that Malaysian experts are alert to this gap and view operationalization, not articulation, as the central challenge.

The practical implementation of ethical AI principles in universities requires five concrete institutional mechanisms. First, AI-specific ethics review committees, analogous to institutional review boards for research ethics, should evaluate proposed AI applications against defined ethical criteria before deployment. These committees should include representatives from academic governance, student services, legal compliance and data governance. Second, mandatory pre-deployment ethical impact assessments should be integrated at defined gate stages (concept approval, pilot evaluation, production scaling). Third, institutional AI policies with explicit enforcement provisions, including defined sanctions, mandatory incident reporting and annual compliance audits, ensure ethical commitments are binding. Fourth, data management practices must incorporate formalized data-lineage tracking (63), bias-testing protocols and contractually enforceable data-quality standards for third-party providers. Fifth, algorithmic audit registries documenting each AI system's purpose, training data, known limitations and bias-test results should be maintained and, where appropriate, published to build stakeholder trust (33, 46–48, 50, 52).

Technology and Workforce as Sequenced Enablers

Technology and Infrastructure [0.80] and Change Management [0.79] are indispensable but their effective deployment is contingent on governance and data foundations (2, 55, 53). The relatively lower priority assigned to these domains should not be misread as evidence of their unimportance; rather, it reflects the panel's judgement that infrastructure and workforce investments deliver returns only when sequenced after governance and data readiness are in place. This sequencing aligns with the broader STS principle that technical subsystems cannot be optimized in isolation from the social subsystems that shape their use (16, 20, 21, 60).

The Change Management domain [0.79] warrants particular attention. Although it received the lowest defuzzified score, expert agreement on its inclusion was high 92%], indicating that the panel views workforce enablement as essential but contingent. AI integration alters not only what universities do but who decides, how decisions are documented and how human-algorithmic responsibilities are distributed; sustained attention to vision clarity, stakeholder engagement, role-based training and AI champion networks is therefore indispensable (30, 53, 54, 57). Without coordinated change management, even technically sound AI deployments tend to encounter resistance, underutilization, or misuse (29, 51). The findings here echo evidence from K-12 and higher-education studies showing that workforce readiness must be treated as an ongoing institutional commitment rather than a pre-launch activity (54, 56, 60). For Malaysian universities, this implies dedicated investment in AI literacy programmes, role-specific upskilling and structured communication channels that translate strategic AI decisions into operational understanding across academic and administrative staff.

Synthesis: Toward a Governance-First Implementation Model

The five domains articulate a coherent governance-first implementation model. Expert consensus supports establishing accountability structures and data readiness as preconditions for responsible technological investment. This sequencing departs from the dominant pattern of AI adoption in higher education, which has tended to begin with tool deployment and treat governance, data, ethics and workforce questions as downstream concerns to be addressed once problems emerge (8, 26). The present findings suggest that this conventional sequence is precisely backwards: institutions that defer governance and data work until after technology deployment accumulate the very pathologies (fragmented accountability, unreliable data, ethical exposure and workforce disengagement) that subsequent governance efforts must then attempt to repair.

The governance-first model also has implications for how universities allocate institutional attention and budget. In practice, capital expenditure on AI platforms is highly visible and politically attractive, while investment in data governance, ethics committees and workforce capability is comparatively invisible. The priority ranking produced here provides empirical support for reallocating institutional attention toward these less visible foundations. Theoretically, this sequencing is consistent with STS theory's warning against technology-led change that prioritizes tool deployment without redesigning the human work systems that use them (21, 22). It also extends the IT governance literature by demonstrating that the governance-first principle, well established in corporate settings, applies with equal force to universities operating under resource constraints (24, 68-70).

Institutional Barriers to AI Readiness

While the framework identifies what must be prioritized, practical implementation is conditioned by institutional barriers. Five are particularly significant for Malaysian universities. First, data interoperability: most universities operate heterogeneous landscapes of legacy systems never designed to exchange data in real time (36, 64, 65). Second, data quality gaps, incomplete records and inconsistent coding conventions mean AI models may be trained on unreliable data (41, 42). Third, privacy and consent management present legal and operational barriers given that Malaysia's PDPA pre-dates the current AI landscape (33, 55). Fourth, cybersecurity exposure is amplified by AI adoption through adversarial inputs, model-inversion attacks and supply-chain risks (38, 55). Fifth, institutional AI readiness (leadership awareness, workforce digital literacy and organizational change capacity) is unevenly distributed (9, 10, 62).

These five barriers do not operate independently. They interact in ways that compound their effect: poor data interoperability worsens data quality problems; weak privacy frameworks heighten cybersecurity exposure; and limited workforce digital literacy undermines institutional capacity to respond to all four preceding barriers. This interaction explains why piecemeal interventions, upgrading one system, drafting one policy, training one cohort, tend to produce disappointing results in Malaysian universities and across the broader Global South (9, 10, 29). The implication is that AI readiness must be approached as a system-level challenge requiring coordinated investment across governance, data, ethics, infrastructure and workforce simultaneously, rather than as a sequence of isolated initiatives.

For Malaysian higher education specifically, the barriers identified here intersect with structural features of the national system. The dual public–private university structure produces significant variation in baseline digital maturity, while centralized oversight through the Malaysian Qualifications Agency and the Malaysia Digital Economy Corporation creates regulatory pressure that universities are not yet equipped to satisfy uniformly (58-60). The Personal Data Protection Act [2010], drafted before generative AI and large-scale algorithmic decision-making became practical realities, leaves substantial uncertainty regarding the legal basis for AI-driven student profiling, predictive analytics and automated administrative decisions (33). Addressing these barriers will therefore require coordinated action not only at the institutional level but also at the national policy level, including updated data protection legislation, AI-specific accreditation criteria and sector-wide capability-building programmes tailored to higher-education governance needs.

Conclusion

This study developed and validated a prioritized framework to guide responsible AI integration in higher education institutions. Using the Fuzzy Delphi Method, expert consensus confirmed that governance, data readiness and ethical safeguards should be established before expanding technological investments.

Study Limitations

Several limitations warrant acknowledgement. The panel comprised twelve experts, which is appropriate for FDM but limits the breadth of perspectives. The study was conducted in the Malaysian context; priority ordering may vary elsewhere. The analysis validated and prioritized domains rather than measuring implementation outcomes. Findings are based on first-round convergence.

A further limitation concerns the level of abstraction at which items were designed. Principles were formulated at a high conceptual level to ensure generalizability, but this raises the possibility that items were framed too broadly, potentially disposing the panel toward agreement. The low distance values (most d values clustered well below [0.15]) are consistent with both genuine convergence and items not being sufficiently contestable. To mitigate this, a pilot review was conducted with three specialists, after which two items were re-worded to introduce sharper trade-offs. Future studies should complement this framework with item-level Likert-scale validation and include trade-off-oriented items to test consensus robustness.

An additional limitation is the temporal sensitivity of AI governance frameworks. The AI landscape is evolving rapidly, with advances in generative AI, large-language-model deployment and multi-modal systems introducing governance challenges not anticipated during data collection. The regulatory environment is also maturing: the EU AI Act, Malaysia's emerging National AI Ethics Code and comparable instruments progressively define new compliance obligations. The framework should therefore be treated as a living artefact subject to periodic revalidation, ideally on an annual basis.

Transferability beyond Malaysia must be addressed with explicit caution along three dimensions. First, governance structures differ substantially: the Malaysian dual public–private system, centralized quality assurance through MQA and national coordination through MDEC create a governance ecosystem not replicated elsewhere. Second, digital development levels vary: the data-infrastructure maturity and digital-literacy baselines assumed here may not hold in lower-income Global South settings. Third, regulatory frameworks diverge: Malaysia's PDPA and emerging AI standards shape governance priorities differently from the EU's GDPR/AI Act regime or conditions in sub-Saharan Africa. While the framework's domain architecture may transfer more readily, the specific priority ranking should be treated as contextually contingent. Multi-country replication studies using the same FDM protocol are recommended (9, 10, 58, 59).

Finally, it is important to distinguish between expert validation and implementation feasibility. The FDM establishes that the panel considers these principles important; it does not demonstrate that the framework can be operationally implemented within the structural, financial and cultural constraints of actual university environments. Expert consensus on importance does not guarantee operational viability: a principle judged essential may face insurmountable barriers in practice. This validation–implementation gap is a fundamental limitation of expert-panel methodologies. Addressing it requires institutional case studies, implementation pilot programmes and longitudinal outcome-measurement research assessing whether framework-guided adoption produces measurable improvements compared to unguided adoption.

Future Prospects

Given the rapid evolution of generative AI capabilities and ongoing regulatory maturation, the framework should be treated as a living artefact. The authors recommend annual review cycles in which domain priorities are reassessed and design principles updated. Future research should apply the framework in institutional case studies, extend it through causal-modelling methods such as DEMATEL or ISM, replicate the study in other Global South contexts and develop outcome-measurement instruments to assess framework-guided implementation effectiveness.

Abbreviations

AHP: Analytic Hierarchy Process, AI: Artificial Intelligence, DEMATEL: Decision Making Trial and Evaluation Laboratory, FDM: Fuzzy Delphi Method, ISM: Interpretive Structural Modeling, MDEC: Malaysia Digital Economy Corporation, MQA: Malaysian Qualifications Agency, PDPA: Personal Data Protection Act, RQ: Research Question, STS: Socio-Technical Systems.

Acknowledgement

We express our sincere thanks to the UNITAR International University for supporting the publication of this research.

Author Contributions

Nurul Aisyah Kamrozzaman: Conceptualization, Writing, Nur 'Izzatty Muhiddin: Data Collection, Data analysis, Washima Che Dan: Proofreading, Fatin Nabilah Abdul Wahid: Conclusion.

Conflict of Interest

The authors declare that there is no conflict of interest for the publication of this paper.

Data Availability

Data are available from the corresponding author upon reasonable request.

Declaration of Artificial Intelligence (AI) Assistance

During the preparation of this manuscript, the authors used ChatGPT to assist with improving grammar, coherence and formatting alignment with journal guidelines. After using this tool, the authors reviewed and edited the content thoroughly to ensure accuracy and originality. The authors take full responsibility for the integrity, analysis and conclusions of the manuscript.

Ethics Approval

The ethics approval number for this study is [UNITAR/REC/2025/001]. Ethics approval and informed consent were obtained for this study. The Fuzzy Delphi exercise involved twelve expert panellists, each of whom provided written informed consent prior to participation, including consent for the use of their anonymized responses in publication. Personal identifiers and institutional affiliations were withheld in accordance with confidentiality protocols. The signed consent letters from all twelve panellists are available from the corresponding author upon request and the study was conducted in accordance with the ethical research guidelines of UNITAR International University.

Funding

This paper is funded by UNITAR International University, Malaysia.

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How to Cite: Kamrozzaman NA, Muhiddin NI, Dan WC, Wahid FNA. A Governance Framework for Responsible AI Integration in Higher Education: A Fuzzy Delphi Study. Int Res J Multidiscip Scope. 2026;7(3):1154-1167. DOI: 10.47857/irjms.2026.v07i03.011001