Predicting International Partnership Readiness: What Institutional Factors Shape AI Integration Capacity in Nigerian Universities' Engineering Programs?

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Abstract

Background. International partnerships increasingly aim to build artificial intelligence (AI) capacity in engineering programs across developing regions, yet evidence-based guidance for designing such partnerships remains scarce. The 2025 United States Agency for International Development (USAID) funding freeze disrupted partnerships across African higher education, exposing the fragility of collaborations selected on reputation or governance type rather than on empirical assessment of institutional readiness. Engineering educators seeking international collaboration need a way to identify institutions positioned for productive, sustainable partnership.

Purpose. This study identifies institutional and contextual factors that predict AI integration and partnership readiness in Nigerian universities, with particular attention to engineering and computing programs as primary sites of AI adoption. The goal is to give international engineering education partners evidence-based criteria for partner selection grounded in institutional profiles rather than governance assumptions.

Design and Method. Comparative content analysis of 45 Nigerian universities stratified by type (15 Federal, 15 State, 15 Private) was conducted from May to October 2025. AI integration was assessed across six dimensions (AI Infrastructure, Curriculum Integration, Research Initiatives, Industry Partnerships, International Collaborations, and Policy Frameworks) using a 10-point coding framework with dimension-specific anchored descriptors. Inter-rater reliability yielded Cohen's kappa of 0.79 to 0.85 across dimensions. Multiple regression identified predictive factors and Pearson correlation with Bonferroni correction examined relationships among dimensions.

Results. The regression model explained 30% of variance in AI integration scores, $R^2=0.30$, $F(4,40)=4.29$, $p=0.006$. Institution age was the strongest predictor, $\beta=0.43$, $p=0.016$, followed by South-West regional location, $\beta=0.31$, $p=0.029$. Institution type, tested via joint F-test on dummy variables, was not a significant predictor when other factors were controlled, $F(2,40)=0.30$, $p=0.744$. A strong correlation between international collaborations and industry partnerships, $r=0.74$, $p<0.001$, indicated mutually reinforcing external networks. Additional analysis showed institution age correlated moderately with Research Initiatives, $r=0.40$, $p=0.006$, and Research Initiatives correlated strongly with overall AI integration, $r=0.89$, $p<0.001$, supporting a resource-based mechanism in which age operates through accumulated faculty research capacity.

Conclusions. These findings challenge assumptions that governance structure alone determines partnership readiness. International engineering education partners should assess specific institutional profiles rather than selecting partners based on institution type. Three evidence-informed strategies are proposed: tiered consortium models, sector-specific partnerships aligned with engineering workforce needs, and hybrid digital-physical approaches that address infrastructure constraints.

Keywords: *partnership readiness, AI integration, Nigerian higher education, engineering education, international collaboration, institutional capacity*

1. Introduction

1.1 The Partnership Challenge

International educational partnerships have become a primary mechanism for building artificial intelligence (AI) capacity in engineering programs across developing regions. Initiatives such as the

University of Michigan's $6 million AI in Science African Faculty Fellows program [1] and Carnegie Mellon University's Africa campus in Rwanda [2] illustrate growing investment in collaborative AI development for engineering and computing education. Yet designing effective partnerships requires understanding what institutional factors predict readiness for successful collaboration, and the evidence base to guide that judgment remains thin.

Recent disruptions have made this gap costly. The 2025 USAID funding freeze halted higher education partnerships across Africa, exposing the vulnerabilities created when collaborations depend on single funding sources without deep institutional grounding [3], [4]. The disruption revealed a pattern: international partners often select collaborators on governance type or reputation rather than on evidence-based readiness factors. For engineering educators at U.S. and other international institutions seeking African partners, this pattern translates into real risk: partnerships that collapse when external funding shifts, because the selected institutions lacked the accumulated capabilities to sustain collaboration on local strength.

1.2 The Nigerian Context

Nigeria offers a strong context for investigating predictors of AI integration and partnership readiness in engineering education. As Africa's most populous nation with over 200 million people and the continent's largest economy, Nigeria's higher education development carries significant regional implications [5]. The Nigerian higher education landscape encompasses approximately 300 universities across three distinct governance structures: Federal universities (n=72) funded by the national government, State universities (n=67) supported by individual state governments, and Private universities (n=160) operated by religious organizations, foundations, or individuals. Each governance type maintains engineering and computing programs that serve as primary sites for AI technology integration.

This institutional diversity creates natural variation in resources, capabilities, and governance approaches. To the authors' knowledge, however, no published study systematically examines what factors predict AI integration capacity across these institutional types. Do Federal universities' resource advantages translate to higher integration in engineering programs? Does private sector agility compensate for fewer resources? What role do geographic location and institutional maturity play? Without answers, international engineering education partners rely on assumptions rather than evidence.

1.3 Research Question and Contributions

This study addresses one focused research question:

> ***RQ:*** *What institutional and contextual factors predict AI integration levels and partnership readiness in Nigerian universities?*

Answering this question produces three contributions to the international engineering education literature. First, the study offers the first empirical analysis of factors predicting AI integration capacity across Nigerian universities, giving engineering educators a baseline for partner assessment. Second, it challenges the assumption that governance structure determines institutional capacity, showing empirically that institutional age and geographic location matter more than whether a university is Federal, State, or Private. Third, it translates these findings into three evidence-informed partnership strategies that international engineering education collaborators can apply when designing sustainable AI-focused initiatives.

This paper focuses on the predictive-factors question and its implications for partnership design, drawing on a broader comparative study by the authors (see Author Note).

2. Background

2.1 Technology Adoption in African Higher Education

Research on technology adoption in African higher education documents both progress and persistent barriers. Recent studies reveal AI applications in career guidance [6], computing education innovations [7], and educational development [8]. Persistent constraints include inconsistent electricity supply and limited internet connectivity [9], [10], human capital gaps in AI expertise [11], and insufficient industry partnerships for experiential learning [12].

Why do some institutions overcome these barriers while others remain stuck? The literature offers several candidates. Institution age may matter because older institutions accumulate resources, expertise, and legitimacy over time [13]. Geographic location may influence access to technology hubs, industry partners, and international networks [14]. Governance structure may shape resource stability and organizational agility [15]. These candidates have not been systematically tested in the Nigerian context.

2.2 International Educational Partnerships

The literature on international educational partnerships emphasizes mutual benefit, capacity development, and local ownership rather than donor-recipient dynamics [16], [17]. Successful partnerships, including AMPATH's collaboration between Indiana University and Moi University [18], the African Research Universities Alliance [19], and the World Bank's Africa Centers of Excellence program [20], share common features: they build on existing institutional strengths, create sustainable local capacity, and align with regional development priorities.

Yet partnership design often relies on institutional reputation or convenience rather than systematic assessment. Understanding what predicts partnership readiness would enable more strategic partner selection. If institutional age matters more than governance type, partners should prioritize established institutions regardless of whether they are Federal, State, or Private. If network connections predict readiness, partners should seek institutions already engaged internationally rather than those operating in isolation.

2.3 Conceptual Framework

This study integrates three theoretical perspectives (Figure 1), namely institutional theory, resource-based view (RBV), and network theory, into a unified conceptual framework. These perspectives are complementary: institutional pressures create motivation for adoption, resources determine capacity to adopt, and networks provide knowledge and support for implementation. The framework guides data collection by identifying observable indicators, shapes analysis by specifying testable predictions, and informs interpretation by explaining observed patterns.

Institutional theory examines how organizational structures, norms, and legitimacy concerns influence technology adoption [15], [21]. Older institutions may have accumulated greater legitimacy, enabling them to attract resources and partnerships that newer institutions cannot access. The framework predicts that institutional age and established legitimacy will positively predict AI integration.

Resource-Based View (RBV) explains how organizational resources and capabilities influence strategic decisions including technology adoption [13], [22]. Institutions accumulate resources over time through government funding, tuition revenue, research grants, and partnership income. These accumulated resources should predict capacity for AI integration independent of governance structure. The framework predicts that resource availability, proxied by institutional age and size, will predict integration levels.

Network theory emphasizes how inter-organizational relationships facilitate knowledge transfer and resource access [14], [23]. Institutions with stronger international ties may develop greater capacity to adopt new technologies through exposure to global practices, access to expertise, and legitimacy derived from international recognition. The framework predicts that international collaborations and industry partnerships will be positively correlated, representing mutually reinforcing network effects.

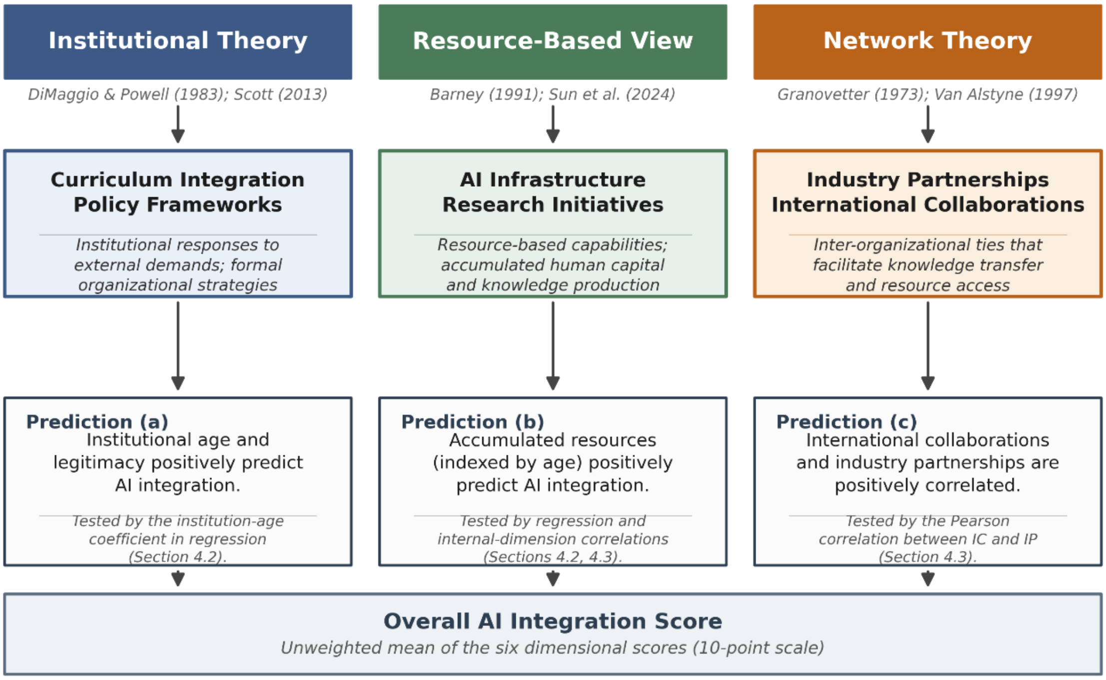

Figure 1. Integrated conceptual framework linking the three theoretical perspectives to the six AI integration dimensions and to testable predictions.

3. Research Design and Methodology

This study employed comparative content analysis [24] to systematically assess AI technology integration across Nigerian universities and identify predictive factors. Figure 2 summarizes the complete methodology framework, including data sources, the five-step data collection protocol, coding procedures, validity measures, and key statistical outputs.

3.1 Sample Selection

At the time of sampling (May 2025), Nigeria's higher education system comprised approximately 300 universities recognized by the National Universities Commission. A total of 45 universities were sampled through equal allocation stratified sampling (15 per institution type) rather than proportional allocation, a choice methodologically grounded in the study's comparative purpose [25], [26]. With 15 institutions per group, the design achieves approximately 80% power to detect medium pairwise effect sizes (Cohen's d=0.50) at α=0.05 [27]. For omnibus three-group comparisons, this sample provides adequate power for large effects while offering more limited sensitivity to medium

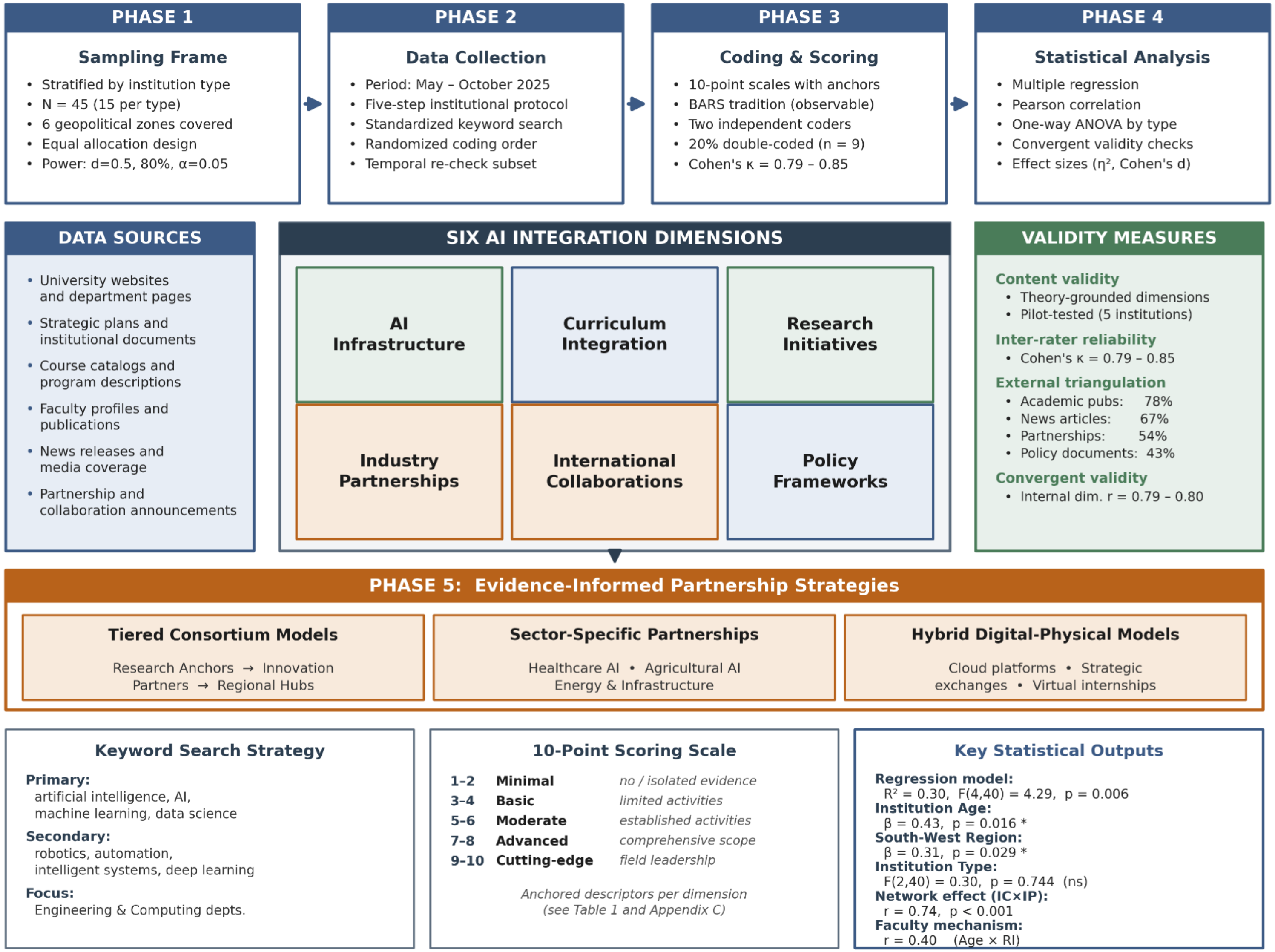

Figure 2. Research methodology framework: five-phase design, six AI integration dimensions, validity measures, and key statistical outputs.

effects, a constraint addressed through reporting effect sizes and confidence intervals alongside significance tests.

Selection criteria included geographic distribution across Nigeria's six geopolitical zones, establishment period variation (1948 to 2023), and information availability. Figure 3 displays Nigeria's geopolitical zones and the distribution of sampled institutions.

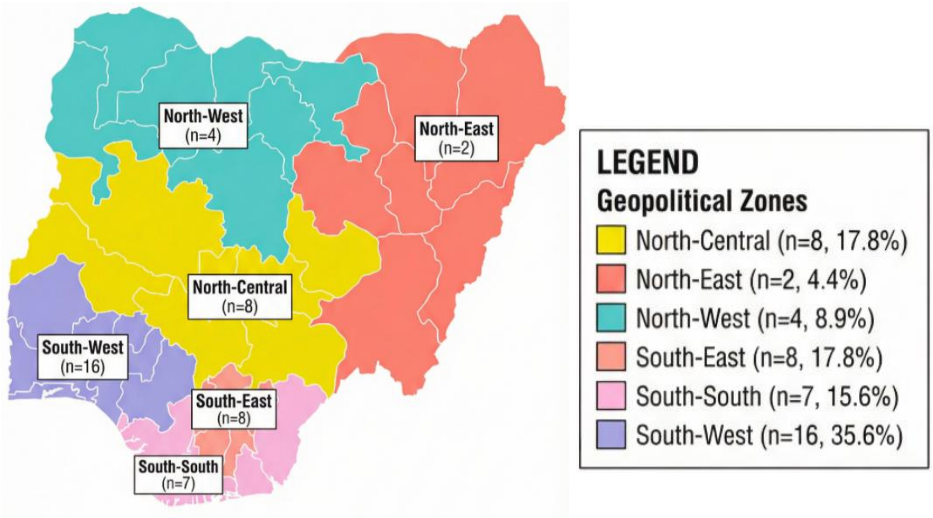

Figure 3. Map of Nigeria's six geopolitical zones and sampled institutions.

3.2 Data Collection

Data were manually collected between May and October 2025 following a standardized protocol. Primary sources included official university websites and affiliated departmental sites, strategic plans and institutional documents where publicly available, course catalogs and academic program descriptions, faculty profiles and research publications, news releases and media coverage of AI-related initiatives, and partnership announcements and collaboration agreements.

Each institution was assessed through a five-step process: (1) systematic review of the main university website; (2) department-level analysis with emphasis on computer science, engineering, and related technical departments, as these fields serve as primary indicators of institutional AI capacity given their direct engagement with AI technologies and their central role in preparing engineers for an AI-transformed workforce; (3) faculty profile assessment examining individual research interests and publications; (4) review of news and events for recent AI-related activities; and (5) identification of collaboration agreements and partnerships. A standardized keyword search strategy employed primary terms (artificial intelligence, AI, machine learning, data science) and secondary terms (robotics, automation, intelligent systems, deep learning). To mitigate temporal inconsistency across the five-month collection window, institutions were assessed in randomized order across strata, and a subset of early-coded institutions was re-examined at the end of the period to verify content stability.

3.3 Coding Framework and Anchored Descriptors

AI integration was assessed across six dimensions that operationalize constructs from all three theoretical perspectives: AI Infrastructure captures resource-based capabilities [13]; Curriculum Integration reflects institutional responses to external demands for AI competencies [15]; Research Initiatives represent accumulated human capital and knowledge production capacity [13], [22]; Industry Partnerships and International Collaborations operationalize network relationships that facilitate knowledge transfer and resource access [14], [23]; and Policy Frameworks capture formal organizational strategies governing technology adoption [21].

A structured 10-point coding framework with anchored descriptors was developed through an iterative process. Because no psychometrically validated instrument specifically designed for comparative scoring of AI integration across African higher education institutions is currently available in the peer-reviewed literature, a context-specific rubric grounded in theory was required. The 10-point scale with five anchored levels follows the behaviorally anchored rating scale (BARS) tradition of reducing rater subjectivity by tying each score band to concrete observable indicators, while preserving sufficient granularity to distinguish institutions at similar developmental stages. Initial dimension definitions and scoring criteria were drafted from the theoretical framework (Section 2.3) and from prior assessments of technology integration in higher education [28], [29], establishing face and content validity through alignment with established conceptual and empirical foundations. These criteria were refined through pilot coding of five institutions (not in the final sample) to clarify anchor definitions and resolve scoring ambiguities. Each dimension uses five anchored levels: 1–2 (Minimal), 3–4 (Basic), 5–6 (Moderate), 7–8 (Advanced), and 9–10 (Cutting-edge). Table 1 presents the dimension-specific anchored descriptors for AI Infrastructure, with representative Nigerian institutions scored at each level to illustrate how the rubric differentiates between adjacent score bands. Complete dimension-specific rubrics for all six dimensions are provided in Appendix C to enable replication of the coding process.

Table 1. Anchored Descriptors and Representative Exemplars: AI Infrastructure Dimension

Level (Score)	Descriptor	Representative Exemplar	Score
Minimal (1–2)	No dedicated AI facilities or equipment; basic computing resources only; no specialized AI software or platforms.	None observed in sample	n/a
Basic (3–4)	General computing labs with some AI software; limited high-performance computing access; basic internet connectivity.	Lagos State University: general computing labs; limited specialized AI infrastructure; reliance on external programs (e.g., LASU–TCRT UK).	3
Moderate (5–6)	Dedicated AI/data-science labs; moderate computing resources; some specialized AI software and tools; reliable internet connectivity.	Obafemi Awolowo University: ICT-Driven Knowledge Park; computing facilities for AI research; conference-hosting capabilities.	6
Advanced (7–8)	Multiple specialized AI facilities; high-performance computing resources; comprehensive AI software suites; cloud computing access; dedicated research equipment.	University of Lagos: AIRLAB (AI and Robotics Lab); NITHub (NITDA Innovation Hub); cloud computing access; comprehensive computing facilities.	8
Cutting-edge (9–10)	State-of-the-art AI research facilities; supercomputing access; full range of AI development tools; advanced robotics labs; industry-standard infrastructure.	None observed in sample	n/a

Note. Exemplars drawn from the coded sample. No sampled institution reached the Cutting-edge (9–10) or the lowest Minimal (1–2) level on AI Infrastructure; observed scores ranged from 1 to 8.

An overall AI integration score was calculated as the unweighted mean of the six dimensional scores, treating each dimension as equally important to comprehensive AI integration. This approach follows established practice in comparative content analysis, where coding frameworks are developed to operationalize theoretical constructs for specific research contexts rather than adopted as standardized instruments [24], [30].

3.4 Statistical Analysis

Analyses were conducted in Python 3.12 using pandas, scipy.stats, and matplotlib. Multiple regression examined predictors of overall AI integration. The model included Institution Age (continuous, 2025 minus establishment year), Geographic Location (binary, South-West region versus other), and Institution Type (dummy-coded with Federal universities as the reference category). This specification yielded four predictors and allows assessment of each factor's independent contribution while controlling for the others. Pearson correlation analysis examined relationships among the six dimensions, with Bonferroni correction applied for multiple comparisons. Statistical significance was set at $\alpha=0.05$.

3.5 Validity, Reliability, and Data Quality

Validity was established through multiple complementary procedures rather than through a single psychometric test, consistent with the content-analysis literature [24], [30]. Content validity was established by drafting anchors from the theoretical framework and prior assessments [28], [29], and refining through pilot coding of five non-sample institutions. Inter-rater reliability was established through independent coding of 20% of institutions (n=9) by two trained researchers; Cohen's kappa values ranged from 0.79 to 0.85 across dimensions, indicating substantial to almost perfect agreement [31]. Discrepancies were resolved through discussion and consensus, with coding guidelines refined accordingly.

External validity was established through source triangulation: coded information was cross-referenced against independent sources where available, with verification rates of 78% for academic publications, 67% for news articles, 54% for partnership announcements, and 43% for government documents. Lower verification rates for partnerships and policy reflect limited public availability of internal governance documents rather than evidence of inaccuracy. Convergent validity is further supported by the strong intercorrelations observed among the internal capability dimensions ($r=0.79$–0.80 among AI Infrastructure, Curriculum Integration, and Research Initiatives; see Section 4.3), consistent with the dimensions measuring related aspects of a coherent underlying construct of institutional AI integration capacity.

Web-presence variation is a known limitation of content analysis [32]. Seven coordinated mitigation steps constrain this bias: (a) multi-source data collection across websites, strategic plans, course catalogs, faculty profiles, news releases, and partnership announcements (Section 3.2); (b) a five-step institutional assessment protocol with emphasis on engineering and computing departments; (c) a standardized keyword search strategy; (d) randomized coding order across strata; (e) temporal stability re-checks on a subset of early-coded institutions; (f) independent external source verification; and (g) inter-rater consensus resolution of scoring discrepancies. Data quality varied across institutions: 55.6% had comprehensive website information, 26.7% had limited information, and 17.8% had accessibility issues addressed through supplementary data collection. Residual limitations of this approach are discussed in Section 7.

3.6 Researcher Positionality

Consistent with recommendations for transparency in research [33], the authors acknowledge positionalities that may influence interpretation. The first author is a Nigerian doctoral candidate in engineering and computing education who completed undergraduate engineering education at a Nigerian state university that is included in the sampled institutions and has since navigated educational and professional systems across five countries (Nigeria, France, United Kingdom, United Arab Emirates, United States). The second author is a Nigerian doctoral candidate in engineering and computing education whose undergraduate engineering training was completed at Enugu State University of Science and Technology (also a sampled state university), with subsequent industry research experience and scholarship on AI applications in West African education [6].

Together, the authors bring an insider-outsider perspective combining lived experience of Nigerian state universities as undergraduates, industry and academic work across the Nigerian higher education landscape, and graduate training in a United States research-intensive university. These positionalities informed interpretation of how institutional factors shape AI adoption while systematic coding procedures and inter-rater reliability checks (Section 3.5) were implemented to mitigate potential biases.

4. Findings

4.1 Sample Characteristics

The final sample comprised 45 Nigerian universities: Federal (n=15, 33.3%), State (n=15, 33.3%), and Private (n=15, 33.3%). Federal universities had the longest establishment history (range: 1948 to 2011; mean year: 1979), followed by State universities (1979 to 2023; mean: 1998) and Private universities (1999 to 2014; mean: 2005). Geographic distribution showed concentration in the South-West (n=16, 35.6%), consistent with historical patterns of university establishment in Nigeria.

4.2 Predictors of AI Integration

Multiple regression identified significant predictors of overall AI integration. The full model explained 30% of variance in integration scores, $R^2=0.30$, Adjusted $R^2=0.23$, $F(4,40)=4.29$, $p=0.006$. In social science research, R^2 values between 0.10 and 0.50 are generally acceptable given the complexity of organizational behavior [34]; the obtained value falls within the moderate range of this benchmark, capturing a meaningful portion of variance while acknowledging that additional unmeasured factors also shape AI integration. Table 2 presents the regression results.

Table 2. Multiple Regression Results: Predictors of Overall AI Integration

Predictor	β	SE	t	p	95% CI
Institution Age	0.43	0.016	2.50	0.016*	[0.01, 0.07]
South-West Region	0.31	0.487	2.27	0.029*	[0.12, 2.09]
Institution Type	n/a	n/a	F(2,40)=0.30	0.744	Joint F-test

*Note. $R^2=0.30$, Adjusted $R^2=0.23$, $F(4,40)=4.29$, $p=0.006$. Institution Type tested via joint F-test for State and Private dummy variables (Federal = reference). *$p < .05$.*

Institution Age was the strongest predictor, $\beta=0.43$, $p=0.016$, with older universities showing higher integration. Each additional decade of institutional history was associated with a 0.43 standard-deviation increase in AI integration scores. This result directly supports RBV predictions: older institutions have accumulated human capital, infrastructure, and organizational capabilities that enable technology adoption [13]. From an institutional-theory perspective, established universities have also accumulated legitimacy that attracts resources and partnerships unavailable to newer institutions [15], [21].

Geographic Location was significant, with South-West universities showing higher integration scores, β=0.31, p=0.029. The South-West region, home to Lagos and Ibadan, is Nigeria's economic and educational hub with greater access to technology infrastructure, industry partners, and international connections. Network theory explains this pattern: geographic proximity to technology hubs facilitates the inter-organizational relationships that enable knowledge transfer and resource access [14].

Institution Type was not significant when controlling for other variables, joint $F(2,40)=0.30$, $p=0.744$. This result challenges the institutional-theory expectation that governance structure would drive adoption through different isomorphic pressures. Instead, accumulated resources and network positions developed over time matter more than formal governance category.

4.3 Network Effects: The Collaboration–Partnership Connection

Correlation analysis revealed strong positive relationships among the six integration dimensions. The internal capability dimensions were tightly interconnected: AI Infrastructure correlated strongly with Curriculum Integration ($r=0.80$, $p<0.001$) and Research Initiatives ($r=0.79$, $p<0.001$), and Curriculum Integration with Research Initiatives ($r=0.79$, $p<0.001$). These robust intercorrelations provide convergent validity evidence that the dimensions measure related aspects of a coherent underlying construct.

From the perspective of external networks, a strong relationship between International Collaborations and Industry Partnerships emerged, $r=0.74$, $p<0.001$. This correlation, the strongest among external-network dimensions, indicates that institutions developing international connections simultaneously build local industry relationships. The finding provides empirical validation for network-theory predictions that inter-organizational ties create cascading benefits: international partnerships expose institutions to global practices and enhance faculty visibility, which in turn attracts local industry attention [14], [23]. Figure 4 displays this relationship.

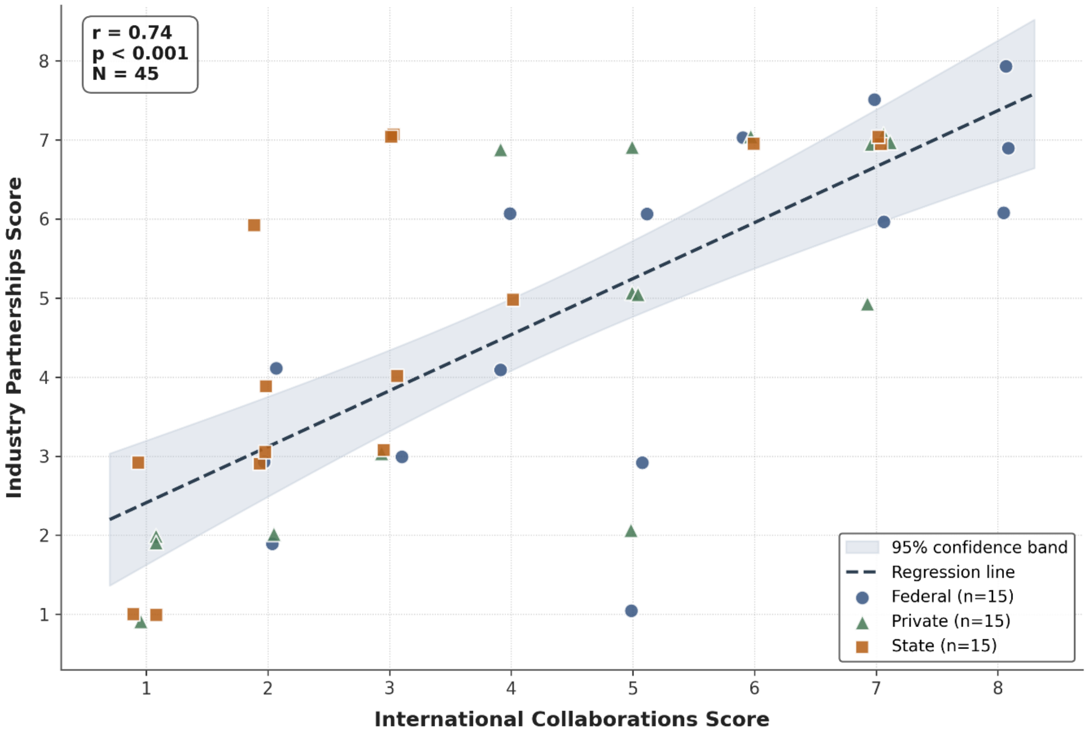

Figure 4. Relationship between International Collaborations and Industry Partnerships scores by institution type ($r=0.74$, $p<0.001$, $N=45$).

4.4 Institution Age, Research Capacity, and AI Integration

The magnitude of the Institution Age coefficient raises a theoretical question about mechanism: does age operate simply as a historical marker, or does it index the accumulated faculty research capacity that RBV identifies as central to competitive advantage [13], [22]? Direct testing of the faculty-capacity mechanism would require per-institution counts of PhD-holding engineering professors and publication histories, which are not available in the present dataset. The Research Initiatives dimension, however, operationalizes faculty research capacity through indicators that would also define faculty seniority in AI: faculty AI research activity, regular AI publications, research groups focused on AI, graduate student AI research, established AI research centers, and significant research funding (see Appendix C, Table C2).

Two supplementary correlations address the mechanism question directly. Institution Age correlated with Research Initiatives, $r=0.40$, $p=0.006$, showing that older institutions accumulate greater research capacity over time. Research Initiatives in turn correlated very strongly with overall AI integration, $r=0.89$, $p<0.001$. Together, these results support the interpretation that institution age influences AI integration in part through accumulated faculty research capacity, consistent with RBV. The age coefficient in the regression can thus be read not as demographic accident but as an index of accumulated human capital that is unevenly distributed across Nigeria's institutional landscape. Direct measurement of per-institution faculty PhD density and research productivity is identified as a priority for follow-up research (Section 7).

4.5 Descriptive Context

For context, overall AI integration levels were moderate, $M=4.79$, $SD=1.71$ on 10-point scales. Federal universities showed the highest mean score, $M=5.25$, $SD=1.64$, followed by Private universities, $M=4.76$, $SD=1.93$, and State universities, $M=4.36$, $SD=1.55$. One-way ANOVA showed no statistically significant differences between institution types, $F(2,42)=1.01$, $p=0.372$, $\eta^2=0.05$, consistent with the regression finding that institution type does not predict integration when other factors are controlled. Figure 5 displays the distribution of integration scores by institution type.

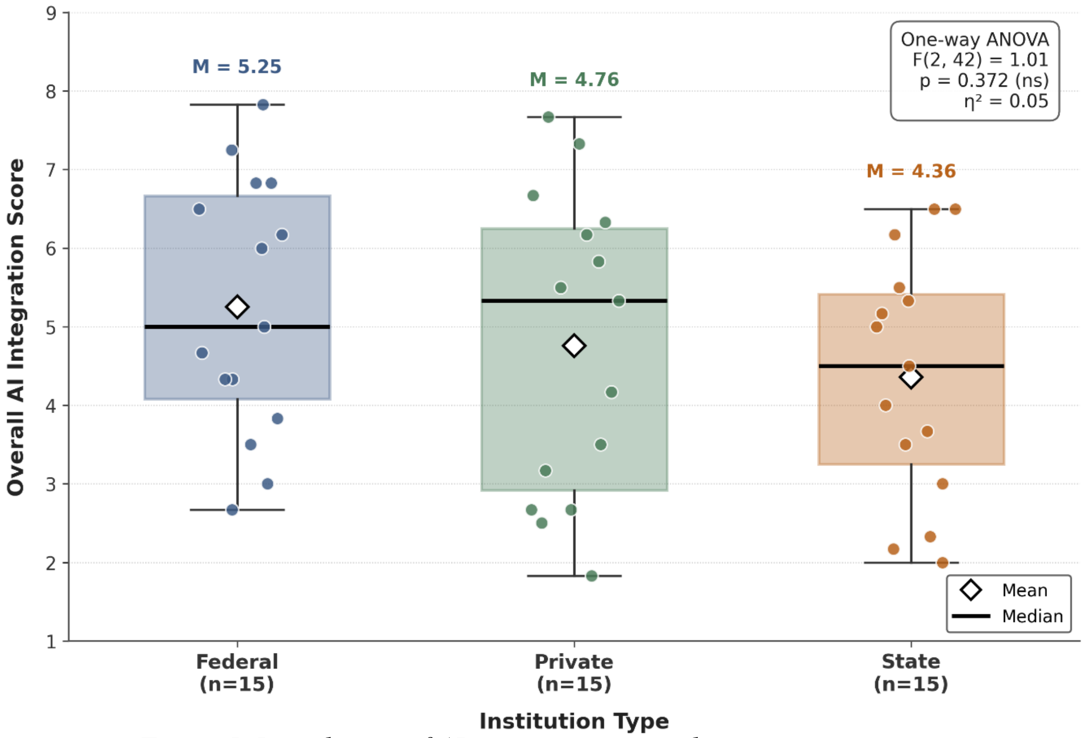

Figure 5. Distribution of AI integration scores by institution type.

Top performers included both Federal and Private institutions: University of Lagos (7.83), Afe Babalola University (7.67), Covenant University (7.33), University of Ibadan (7.25), and Ahmadu Bello University (6.83). The presence of both governance types among top performers reinforces that factors beyond governance structure determine partnership readiness.

5. Discussion

5.1 Rethinking Partner Selection

The result that institution type was not significant after controlling for age and location has practical consequences for international engineering education partnerships. Partners often assume Federal universities offer better collaboration opportunities due to government backing and research mandates, or that Private universities are too resource-constrained for meaningful partnership. The findings challenge both assumptions and extend prior research on technology adoption in developing contexts [9], [10] by showing that governance structure matters less than accumulated institutional capacity.

What matters more is institutional maturity and geographic positioning. A 40-year-old State university in Lagos may offer stronger partnership readiness than a 15-year-old Federal university in a northern state, despite governance-based assumptions. Partners should therefore evaluate specific institutional profiles, including establishment history, location, existing network connections, and demonstrated capacity across relevant dimensions, rather than filtering by institution type.

5.2 The Network Multiplier Effect

The strong correlation between international collaborations and industry partnerships ($r=0.74$) points to what can be termed a network multiplier effect. Institutions developing strong international connections simultaneously develop robust local industry relationships. This aligns with network-theory predictions [14], [23] and extends prior findings on international partnership dynamics [17] by quantifying the linkage. Several mechanisms can plausibly explain the pattern: international partners often facilitate local industry connections through their own networks [35]; globally engaged faculty attract industry attention through enhanced visibility; and capabilities developed through international collaboration enhance attractiveness to industry partners.

In light of the 2025 USAID disruption [3], this network multiplier points toward a concrete sustainability strategy. International collaborations anchored in local industry relevance create triangular partnerships in which local industry partners provide context, data, and funding continuity while international partners contribute expertise and global networks. For engineering programs specifically, industry connections provide experiential learning, research funding, and employment pathways for graduates. Such triangulated partnerships may prove more resilient than bilateral arrangements dependent on single funding sources.

5.3 Geographic Considerations

The significance of South-West location reflects historical patterns of educational resource concentration in the Lagos–Ibadan corridor. Federal universities in this region benefit from consistent government funding through mechanisms such as the Tertiary Education Trust Fund (TETFund), which supports sustained infrastructure investment [36]. Partners committed to equitable development might consider consortium models that pair well-resourced South-West institutions with developing institutions in underserved regions, enabling knowledge transfer and resource sharing while building capacity across geographic areas.

5.4 Transferability to Other African and Global South Contexts

Although this study focuses on Nigeria, the findings have implications across Africa and the broader Global South. The three mechanisms identified (accumulated institutional resources, geographic proximity to economic hubs, and mutually reinforcing network connections) are not Nigeria-specific. Countries with similar higher education structures featuring multiple governance types, including Kenya, Ghana, South Africa, and India, may exhibit comparable patterns where institutional maturity and location predict technology integration capacity more reliably than governance category [37], [38].

The partnership strategies proposed in Section 6 are designed for transferability: tiered consortium models can be adapted by identifying anchor institutions in any national context based on establishment history and demonstrated capacity; sector-specific partnerships can align with each country's priority development sectors and engineering workforce needs; and hybrid digital-physical models address infrastructure constraints common across developing regions, not unique to Nigeria [9], [10]. International engineering education partners working in other contexts can apply the assessment approach developed here: evaluate partners on institutional age, geographic positioning relative to economic centers, and existing network connections rather than using governance type as a proxy for capacity.

6. Implications: Evidence-Informed Partnership Strategies

Three partnership strategies follow from the findings. These strategies draw on successful models in the international partnership literature [16], [17], [20] and address the specific needs of engineering programs building AI capacity.

6.1 Tiered Consortium Models

Rather than single-institution partnerships, international engineering education collaborators should consider tiered consortium approaches that leverage complementary institutional strengths, organized around demonstrated capacity rather than governance type. Research Anchors are established institutions (40+ years) with strong engineering research capacity and international collaboration experience serving as primary research partners; their accumulated legitimacy and resources position them for intensive faculty exchange and joint research in AI applications relevant to engineering disciplines. Innovation Partners are institutions demonstrating curriculum agility and industry orientation, regardless of governance type; their organizational flexibility enables rapid development of AI-integrated engineering curricula and technology transfer initiatives. Regional Development Hubs are institutions in underserved regions with connections to state governments, extending partnership impact to regional engineering workforce development priorities.

6.2 Sector-Specific Partnerships

The variation in institutional strengths indicates value in sector-specific partnership design aligned with Nigeria's engineering workforce needs [17]. Healthcare AI partnerships with institutions having strong biomedical engineering programs and health system connections address AI applications in medical device development, diagnostic imaging, and health informatics. Agricultural AI collaborations with institutions in agricultural regions address precision farming, supply chain optimization, and food processing automation. Energy and Infrastructure partnerships with institutions demonstrating strong civil and electrical engineering programs address AI applications in smart grid management, renewable energy optimization, and infrastructure monitoring systems critical to Nigeria's development.

6.3 Hybrid Digital-Physical Models

Given infrastructure variability (AI Infrastructure showed substantial variance, SD=2.11), engineering education partnerships should incorporate hybrid approaches that address the practical constraints documented in prior work on African higher education [9], [10], [39]. Cloud-based collaboration platforms enable routine research collaboration and curriculum co-development without extensive local infrastructure investment, allowing engineering students to access computational resources for AI projects. Strategic physical exchanges concentrate intensive laboratory training, equipment access, and relationship building in focused periods rather than requiring sustained physical presence. Virtual internship programs address the industry partnership gap [12] by connecting engineering students with international industry partners through remote experiential learning in AI-related engineering roles.

7. Limitations and Future Research

Four limitations should be acknowledged. First, reliance on publicly available information may underestimate AI integration at institutions with limited web presence. Data quality varied across institutions, with 17.8% of sampled institutions presenting accessibility issues; these were addressed through supplementary data collection but cannot fully substitute for comprehensive public documentation. The structured multi-source protocol (Section 3.2), anchored-descriptor rubric (Section 3.3), inter-rater reliability checks (Section 3.5), and external verification rates (Section 3.5) collectively constrain but do not eliminate this limitation.

Second, construct validity was established through convergent lines of evidence: theoretical triangulation across three complementary perspectives (institutional theory, RBV, and network theory), content validity grounded in prior literature and refined through iterative pilot testing, inter-rater reliability of 0.79 to 0.85 (substantial to almost perfect agreement), external source verification at rates of 43% to 78% by source type, and convergent validity indicated by strong intercorrelations among the internal capability dimensions ($r=0.79$ to 0.80). Nonetheless, the authors are not aware of a psychometrically validated instrument specifically for comparative scoring of AI integration across African higher education institutions that would allow the coding framework to be benchmarked against an external standard. Developing and psychometrically validating such an instrument, for example through confirmatory factor analysis on a larger cross-national sample, is identified as a worthwhile methodological contribution in its own right.

Third, the sample size of 45 institutions, while adequate for medium-effect pairwise tests (Section 3.1), limits the robustness of more complex modeling and the generalizability of regression coefficients. The regression's explained variance ($R^2=0.30$) is consistent with acceptable ranges in social science research on organizational behavior [34] but indicates that additional institutional, disciplinary, or individual-level factors not captured here also shape AI integration. Larger-sample replications, including the full population of Nigerian universities with accessible data, would strengthen the evidence base.

Fourth, the cross-sectional design captures integration at a single point in the rapid AI development cycle. Longitudinal designs tracking integration over time would reveal adoption trajectories and would allow tests of whether the predictive factors identified here translate to partnership outcomes over time.

Priorities for follow-up research include: (1) direct measurement of faculty research capacity through per-institution counts of PhD-holding engineering professors, faculty publication indices, and research grant histories, to test the age-as-proxy mechanism articulated in Section 4.4; (2) qualitative studies of faculty, administrator, and student experiences to illuminate implementation challenges beyond institutional-level analysis; and (3) comparative cross-national studies testing whether institutional age and geographic location predict AI integration capacity similarly in Kenya, Ghana, South Africa, or India.

8. Conclusion

The 2025 USAID funding freeze exposed what the engineering education community had underestimated: international partnerships built on single funders rather than on institutional capacity are fragile, and their collapse imposes real costs on the Nigerian and African engineering programs that came to depend on them. The findings reported here offer a path toward more durable partnerships. Two empirical findings anchor the contribution. First, institution type does not significantly predict AI integration once institutional age and geographic location are accounted for; governance category, the heuristic that has often shaped partnership selection, does not map to institutional capacity. Second, international collaborations and industry partnerships are strongly correlated ($r=0.74$), revealing a network multiplier effect. The authors suggest that international engineering education partners move from governance-type filtering toward evidence-based partner assessment. The three strategies proposed here are not prescriptive templates but starting points for dialogue with Nigerian and other African engineering programs about what durable, mutually beneficial AI collaboration can look like in their contexts. The authors look forward to working with engineering education partners across and beyond the African continent to test these strategies in practice, extend the assessment framework to other national contexts, and build the partnership infrastructure that this moment requires.

Author Note

This conference paper is part of a broader comparative study of AI integration across Nigerian universities conducted by the authors. A related full manuscript, "Institutional Structures, Digital Inequality, and AI Integration in Higher Education: Evidence from a Comparative Analysis of Nigerian Universities," is currently under peer review. The present conference paper focuses specifically on predictive factors for partnership readiness and evidence-informed strategies for international engineering education collaboration, using the same underlying dataset as the related manuscript but with a substantively independent framing, research question, and practical contribution. Complete dimension-specific coding rubrics are provided in Appendix C of this paper; the complete dimensional scores for all 45 sampled institutions are available from the authors upon request.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work the authors used GenAI to check internal consistency across manuscript sections and to improve language and readability. After using these tools, the authors reviewed and edited all content as needed and take full responsibility for the content of the published article.

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Appendix A. Sample Distribution by Institution Type and Region

Region	Federal	State	Private	Total	%
South-West	5	4	7	16	35.6
South-East	3	3	2	8	17.8
North-Central	3	2	3	8	17.8
South-South	2	3	2	7	15.6
North-West	2	2	0	4	8.9
North-East	0	1	1	2	4.4
Total	**15**	**15**	**15**	**45**	**100.0**

Appendix B. General AI Integration Scoring Rubric

Score Range	Level	Criteria
1–2	Minimal	No evidence or only isolated, incidental references to AI-related activities.
3–4	Basic	Limited, foundational activities with minimal scope or institutional investment.
5–6	Moderate	Established activities with moderate scope and evident institutional commitment.

Score Range	Level	Criteria
7–8	Advanced	Comprehensive activities with significant scope and dedicated resources.
9–10	Cutting-edge	Activities demonstrating innovation beyond standard practice and field leadership.

This general rubric was applied across all six AI integration dimensions. Dimension-specific anchored descriptors and institutional exemplars for AI Infrastructure are shown in the main text (Table 1). Complete dimension-specific rubrics for all six dimensions are provided in Appendix C.

Appendix C. Complete Dimension-Specific Anchored Rubrics

The tables below present the anchored descriptors used to score each of the five AI integration dimensions not shown in the main text (the AI Infrastructure rubric with institutional exemplars appears as Table 1). Together with Appendix B and Table 1, these descriptors provide the complete coding framework necessary for replication in other national contexts.

Table C1. Anchored Descriptors: Curriculum Integration

Level (Score)	Anchored Descriptor
Minimal (1–2)	No AI-specific courses or programs; limited mention of AI in existing courses.
Basic (3–4)	One or two introductory AI courses; AI topics covered within computer science programs; basic programming courses with AI components.
Moderate (5–6)	Multiple AI courses across programs; AI specialization tracks available; undergraduate AI concentration; cross-disciplinary AI applications.
Advanced (7–8)	Dedicated AI degree programs at undergraduate or graduate level; comprehensive AI curriculum; multiple specialization areas; industry-relevant AI training.
Cutting-edge (9–10)	Full range of AI degree programs at all levels; curriculum aligned with international standards; continuous curriculum updates; industry partnerships in curriculum development.

Table C2. Anchored Descriptors: Research Initiatives

Level (Score)	Anchored Descriptor
Minimal (1–2)	No evidence of AI research; limited faculty expertise in AI.
Basic (3–4)	Individual faculty AI research; occasional AI publications; basic research projects.
Moderate (5–6)	Multiple AI research projects; regular AI publications; research groups focused on AI; graduate student AI research.
Advanced (7–8)	Established AI research centers; significant research funding; high-impact publications; international research collaborations.
Cutting-edge (9–10)	Leading AI research programs with major grants; international recognition; extensive industry research partnerships; policy-influencing research.

Table C3. Anchored Descriptors: Industry Partnerships

Level (Score)	Anchored Descriptor
Minimal (1–2)	No documented industry partnerships for AI; limited engagement with private sector.
Basic (3–4)	One or two industry relationships; occasional guest lectures or workshops; basic internship arrangements.
Moderate (5–6)	Multiple industry partnerships; formal MOUs with technology companies; student placement programs; industry-sponsored events.
Advanced (7–8)	Extensive industry partnership network; joint research projects; industry-funded labs or centers; regular technology transfer activities.
Cutting-edge (9–10)	Strategic industry alliances with major technology firms; co-developed programs; significant industry funding; commercialization track record.

Table C4. Anchored Descriptors: International Collaborations

Level (Score)	Anchored Descriptor
Minimal (1–2)	No documented international collaborations for AI; limited foreign engagement.
Basic (3–4)	One or two international relationships; occasional visiting scholars; participation in international conferences.
Moderate (5–6)	Multiple international partnerships; faculty exchange programs; joint publications with foreign researchers; international grant applications.
Advanced (7–8)	Extensive international collaboration network; joint degree programs; significant international funding; hosting international events.
Cutting-edge (9–10)	Strategic alliances with leading global institutions; major international research programs; international recognition and leadership roles.

Table C5. Anchored Descriptors: Policy Frameworks

Level (Score)	Anchored Descriptor
Minimal (1–2)	No AI-specific policies or strategies; limited mention of AI in institutional planning.
Basic (3–4)	AI mentioned in general technology or digital transformation plans; basic ethical guidelines; informal governance structures.
Moderate (5–6)	Formal AI strategy documents; designated AI governance responsibility; guidelines for AI use in teaching and research.
Advanced (7–8)	Comprehensive AI policy framework; dedicated AI governance committee; ethical guidelines and implementation plans; resource allocation for AI.
Cutting-edge (9–10)	Sector-leading AI policies; regular policy review and updates; integration with national or continental AI strategies; policy influence beyond institution.