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Article

The AI-Native University: A Conceptual Framework and Maturity Model for AI Transformation in Higher Education

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Abstract: Artificial intelligence (AI) is transforming higher education rapidly through advances in generative AI, learning analytics, intelligent tutoring systems, and AI-assisted decision support. Though universities increasingly adopt AI for teaching, learning, assessment, research, and administrative activities, the implementation often remains fragmented and focused on specific applications. Existing research has made significant contributions to areas such as Artificial Intelligence in Education (AIEd), learning analytics, educational data mining, smart universities, and digital transformation. Despite these advances, a very limited attention has been given to conceptualizing artificial intelligence as a strategic institutional capability that connects teaching, learning, assessment, research, administration, and governance within a coherent university-wide framework.

To address this gap, the present study introduces the concept of the AI-Native University (AINU). The AI-Native University refers to a higher education institution in which artificial intelligence is not treated as a standalone technology or a collection of isolated applications, but as a core institutional capability embedded across academic, administrative, and governance functions. At the same time, AI implementation remains guided by human oversight, ethical principles, institutional governance, and the broader educational mission of the university. Drawing on insights from Artificial Intelligence in Education (AIEd), digital transformation, socio-technical systems theory, and human–AI collaboration research, this study develops a conceptual framework that explains how universities can move from fragmented AI adoption toward a more integrated and institution-wide approach to AI-enabled transformation.

The proposed framework includes five key areas where AI can influence university operations: teaching, learning, assessment, research, and institutional management. These areas are supported by several enabling factors, including appropriate infrastructure, governance mechanisms, ethical guidelines, quality assurance processes, cybersecurity measures, and faculty development initiatives. The paper also outlines a maturity pathway that can help institutions understand their current level of AI adoption and plan future development. In addition, it discusses some of the challenges and risks associated with AI implementation and highlights implications for university leaders, policymakers, and researchers.

This study contributes to the ongoing discussion on AI in higher education by introducing the idea of the AI-Native University as a distinct institutional model. It also extends existing thinking on digital transformation in the context of generative AI and emphasizes the growing importance of human–AI collaboration at the institutional level. Finally, the proposed maturity approach offers a starting point for evaluating AI readiness and guiding future transformation efforts. The framework can serve as a foundation for future empirical studies, institutional benchmarking, and policy development.

Keywords: Artificial Intelligence in Education; Generative AI; Higher Education; AI-Native University; Digital Transformation; Learning Analytics; Academic Governance; Responsible AI

1. Introduction

Higher education has repeatedly adapted to technological and societal change, moving from predominantly face-to-face, instructor-centered models toward digitally mediated learning ecosystems supported by learning management systems, online delivery, cloud infrastructure, and analytics-enabled administration (Bates, 2019; Bond et al., 2018). The current wave of artificial intelligence adoption, particularly the rise of generative AI and large language models, differs from earlier waves of educational technology because it does not merely digitize existing processes; it has the capacity to participate in knowledge production, content generation, feedback, reasoning support, and decision assistance across multiple institutional functions (Dwivedi et al., 2023; Kasneci et al., 2023; UNESCO, 2023).

In universities worldwide, students increasingly use AI systems for drafting, brainstorming, coding, summarizing, and language support, while faculty employ AI-assisted tools for lesson design, feedback generation, assessment support, and research assistance (Crompton and Burke, 2023; Zawacki-Richter et al., 2019). At the same time, administrators are exploring AI for enrollment forecasting, retention analytics, resource allocation, and strategic planning (Daniel, 2015; Ifenthaler and Yau, 2020). These developments signal more than the adoption of isolated tools; they indicate the emergence of a new institutional condition in which AI may become foundational to academic operations.

Yet most institutional responses remain fragmented. Universities frequently deploy AI through disconnected initiatives such as chatbots, plagiarism detection systems, adaptive learning platforms, and analytics dashboards, often without integrated governance, shared operating models, or coherent pedagogical redesign (Selwyn, 2019; Williamson and Eynon, 2020). As a result, institutions face persistent concerns regarding academic integrity, data governance, bias, privacy, faculty readiness, vendor dependency, and organizational alignment (Bozkurt, 2023; Holmes et al., 2022; UNESCO, 2023).

The term **AI-Native University (AINU)** is intentionally used in this study to distinguish the proposed concept from related notions such as *AI-enabled*, *AI-powered*, or *intelligent* universities. AI-enabled universities typically employ artificial intelligence within selected functions, including learning analytics, student support, assessment, or administrative services (Holmes et al., 2022; Kasneci et al., 2023). Similarly, AI-powered institutions may utilize advanced AI tools to improve efficiency, personalization, and decision-making without fundamentally transforming institutional structures and processes (Dwivedi et al., 2023). In contrast, an AI-Native University is defined as a higher education institution in which artificial intelligence is embedded as a foundational institutional capability across teaching, learning, assessment, research, administration, and governance. Supported by appropriate infrastructure, governance mechanisms, ethical safeguards, human oversight, and organizational redesign, AI becomes an integral component of how the institution creates value, delivers education, conducts research, and manages operations. This perspective is consistent with emerging views of AI as an organizational capability and a catalyst for human–AI collaboration and institutional transformation (Raisch and Krakowski, 2021; Jarrahi et al., 2022). The term *AI-Native* therefore emphasizes institution-wide integration, strategic alignment, and human–AI collaboration rather than the isolated adoption of AI tools, representing a new stage in higher education transformation.

It is also important to distinguish the present use of “AI-Native” from its emerging usage in the management and strategy literature, where the term “AI-Native organization” or “AI-Native enterprise” typically denotes firms architected from inception around AI-driven products, data pipelines, and automation-first operating models (Iansiti and Lakhani, 2020). That literature centers on competitive advantage, product velocity, and algorithmic decision-making in commercial settings, with comparatively little attention to pedagogy, academic governance, or the public-good mission distinctive to higher education. The AI-Native University concept developed here borrows the structural logic of pervasive, foundational AI integration from this strategy literature but reframes it specifically for the university context, where human oversight, academic freedom, epistemic accountability, and institutional governance are not optional constraints on efficiency but constitutive features of the model itself. This distinction positions AINU as a higher-education-specific theoretical construct rather than a direct import of a commercial management concept.

The objectives of this paper are fourfold. First, it synthesizes the evolution of higher education through digital transformation, smart university development, and AI adoption. Second, it identifies limitations in existing conceptualizations of AI use in higher education. Third, it develops a multi-layer AI-Native University framework. Fourth, it outlines implementation requirements, policy implications, and a future research agenda. In doing so, the paper seeks to provide a strategic and theoretical foundation for universities, policymakers, and researchers seeking to understand and govern institution-wide AI transformation.

To guide the development of the proposed framework and address the identified research gap, the study is structured around the following research questions:

RQ1: What limitations exist within current conceptualizations of AI adoption in higher education?

RQ2: How can AI be conceptualized as an institution-wide capability rather than a collection of isolated applications?

RQ3: What organizational, technological, and governance dimensions characterize an AI-Native University?

RQ4: How can universities assess and advance their progress toward AI-Native transformation?

To address these questions, the study adopts a conceptual framework development methodology based on a structured synthesis of literature from Artificial Intelligence in Education, learning analytics, digital transformation, smart universities, and responsible AI. The resulting framework integrates these perspectives into a unified model of the AI-Native University.

2. Background: Higher Education in the Age of AI

The historical evolution of higher education can be understood as a sequence of institutional adaptations to changing knowledge regimes, technologies, and social expectations. Traditional universities emphasized in-person teaching, disciplinary knowledge transmission, and campus-bound infrastructures. The emergence of information and communication technologies introduced digital libraries, computer-assisted instruction, and web-based resources, gradually expanding access and reconfiguring teaching and administration (Means et al., 2014; Bates, 2019).

A subsequent phase involved the rise of the *digital university*, characterized by virtual learning environments, online and blended teaching, enterprise systems, cloud services, and data-driven administration (Bond et al., 2018; OECD, 2021). Learning management systems such as Moodle, Blackboard, and Canvas became central to educational delivery, while institutions increasingly adopted analytics to monitor progression, engagement, and risk (Siemens and Long, 2011; Gašević et al., 2015).

The *smart university* concept expanded this trajectory by incorporating Internet of Things (IoT) infrastructures, big data platforms, intelligent campus systems, and real-time decision support (Coccoli et al., 2014; Alkhammash et al., 2020). Smart university models typically emphasize connected infrastructure, operational efficiency, predictive analytics, and service integration. However, much of this literature remains weighted toward infrastructure and campus intelligence rather than deep academic redesign.

The emergence of GenAI introduces a distinct qualitative shift. Unlike many earlier educational technologies, generative systems can create explanations, examples, assessments, research summaries, code, simulations, and administrative outputs in natural language and other modalities (OpenAI, 2023; Kasneci et al., 2023). This capability challenges traditional divisions between support tools and core academic work, raising new questions about teaching roles, authorship, feedback, assessment validity, institutional accountability, and the nature of educational value itself (Selwyn, 2024; Tlili et al., 2023).

Accordingly, universities are no longer dealing only with digitalization; they are confronting the possibility of **AI-Native institutional redesign**. This emerging reality provides the context for examining existing scholarship on AI adoption in higher education.

The broader evolution of higher education from traditional universities to digital, smart, AI-enabled, and ultimately AI-Native Universities is summarized in **Appendix C**. This evolution highlights the progressive shift from technology-supported operations toward institution-wide AI integration as a strategic capability.

3. Literature Review

3.1 Artificial Intelligence in Education

Artificial Intelligence in Education (AIEd) is an interdisciplinary field combining computing, learning sciences, cognitive psychology, and instructional design to create systems that support teaching and learning (Holmes et al., 2019; Luckin et al., 2016). Early work focused on intelligent tutoring systems, learner modeling, feedback engines, and adaptive pathways. Over time, advances in machine learning, natural language processing, and recommender systems broadened applications to include automated writing evaluation, dialogue-based tutoring, adaptive sequencing, and personalized support (Woolf, 2010; Roll and Wylie, 2016).

Systematic reviews show growing attention to AI applications in higher education, including profiling and prediction, intelligent tutoring, assessment, and adaptive systems (Zawacki-Richter et al., 2019; Crompton and Burke, 2023). However, much of this body of work is application-specific rather than institution-wide.

3.2 Learning Analytics and Educational Data Mining

Learning analytics concerns the measurement, collection, analysis, and reporting of data about learners and learning contexts for the purpose of improving learning and the environments in which it occurs (Siemens, 2013; Siemens and Long, 2011). Educational data mining complements this field by emphasizing computational pattern discovery from educational datasets (Baker and Inventado, 2014; Romero and Ventura, 2020). These traditions have enabled student risk prediction, engagement monitoring, feedback systems, and evidence-based intervention (Ifenthaler and Yau, 2020; Viberg et al., 2018).

Despite their value, learning analytics implementations often remain siloed within specific platforms, schools, or student-success units. Governance, interoperability, ethics, and integration with institutional decision systems remain unevenly developed (Gašević et al., 2015; Prinsloo and Slade, 2017).

3.3 Generative AI in Higher Education

The release of high-performing large language models accelerated scholarly attention to AI in higher education. GenAI tools have been associated with benefits such as personalized support, multilingual assistance, rapid content generation, formative feedback, and research assistance (Dwivedi et al., 2023; Kasneci et al., 2023; Strielkowski et al., 2025). They also introduce substantial risks, including hallucinated information, fabricated references, hidden bias, overreliance, and new forms of academic misconduct (Bozkurt, 2023; Tlili et al., 2023; UNESCO, 2023).

Current scholarship on GenAI in higher education has grown rapidly, but much of it is exploratory, normative, or focused on classroom use and assessment implications rather than institution-level transformation (Chan and Hu, 2023; Lim et al., 2023; García-Peñalvo, F. J. 2024).

3.4 Digital Transformation in Higher Education

Digital transformation in universities involves more than technology adoption; it entails organizational change in structures, culture, strategy, and value creation (Bond et al., 2018; Benavides et al., 2020). Existing models of digital transformation address infrastructure modernization, digital pedagogy, service redesign, and institutional capability building. However, most such frameworks were formulated before the widespread availability of advanced GenAI and therefore do not adequately address algorithmic governance, foundation models, synthetic content, or AI-mediated academic work (García-Peñalvo, F. J. 2024; Selwyn, 2024).

3.5 Smart Universities and Intelligent Campuses

The smart university literature emphasizes connected systems, ubiquitous computing, analytics-enabled operations, and technology-supported campus experiences (Coccoli et al., 2014; Kwok, 2015). Although useful for understanding infrastructure and operational intelligence, these models generally under-specify pedagogy, assessment redesign, research augmentation, and AI governance across the full institutional stack.

3.6 Responsible AI, Ethics, and Governance

Responsible AI scholarship highlights fairness, transparency, accountability, explainability, contestability, and human oversight as essential principles for AI deployment (Floridi and Cowls, 2019; Jobin et al., 2019; OECD, 2019). In educational settings, these concerns intersect with privacy, student autonomy, profiling, consent, academic freedom, and epistemic trust (Prinsloo and Slade, 2017; Holmes et al., 2022). For higher education institutions, this means AI adoption cannot be assessed solely through performance or efficiency metrics; it must also be governed in relation to institutional mission and public value.

3.7 Research Gap

The literature suggests five key deficiencies:

- First, most studies focus on isolated AI applications, not institution-wide transformation (Zawacki-Richter et al., 2019; Crompton and Burke, 2023).
- Second, many digital transformation frameworks predate GenAI, leaving them under-equipped to address AI-Native workflows and governance (Bond et al., 2018; García-Peñalvo, F. J. 2024).

- Third, smart university models largely emphasize infrastructure and operations rather than full pedagogical and academic integration (Coccoli et al., 2014).
- Fourth, there is limited theorization of human–AI collaboration as an institutional operating principle rather than a task-level interaction. Existing studies frequently examine AI as a tool for supporting specific educational activities, such as tutoring, grading, or content generation, but provide limited insight into how humans and AI systems may collaboratively shape institutional processes, decision-making structures, and organizational capabilities at scale (Luckin, 2018; Holmes et al., 2022; Jarrahi et al., 2022; Raisch and Krakowski, 2021). As AI systems become increasingly autonomous and capable of coordinating complex workflows, understanding institution-level human–AI collaboration becomes essential for future higher education transformation.
- Fifth, few frameworks jointly address teaching, learning, assessment, research, administration, and governance in a single conceptual architecture.

This paper addresses these gaps by proposing a comprehensive AI-Native University framework.

3.8 Positioning the AI-Native University Concept

The concepts of the digital university, smart university, and AI-enabled university have provided important perspectives for understanding technological transformation in higher education. Digital university models primarily focus on the digitization of academic and administrative processes, while smart university frameworks emphasize intelligent infrastructure, data-driven decision-making, and connected campus ecosystems. More recently, AI-enabled universities have emerged through the adoption of artificial intelligence applications in areas such as learning analytics, student support, automated assessment, and administrative services. Although these models have significantly advanced the integration of technology within higher education, they generally conceptualize AI as a supporting technology rather than as a foundational institutional capability.

It is also important to distinguish the AI-Native University concept from the term "AI-Native" as it is used in the business-strategy and software-engineering literatures, where it typically denotes an organization or system built from the ground up around AI-driven products, agentic workflows, or AI-first engineering pipelines, and where removing AI would cause the underlying business model or codebase to fail (Hassan et al., 2024). That usage is technology- and product-centric and originates outside higher education. The AI-Native University, by contrast, is an institutional and governance construct: it is concerned with how teaching, learning, assessment, research, administration, and governance are reorganized around AI as a shared institutional capability, under sustained human oversight, ethical safeguards, and educational mission, rather than with the technical architecture of any single AI product or platform. The shared terminology reflects a parallel intuition across sectors—that mature AI adoption requires structural rather than incremental change—but the institutional, multi-stakeholder, and mission-bound nature of universities means the AINU construct cannot be reduced to, or directly imported from, the enterprise AI-Native literature.

The AI-Native University proposed in this study represents a distinct stage in the evolution of higher education institutions. Rather than viewing AI as a collection of tools deployed within selected functions, the AI-Native University treats artificial intelligence as an institution-wide capability embedded across teaching, learning, assessment, research, administration, and governance. In this model, AI is integrated into strategic planning, operational processes, decision-making structures, and academic practices while remaining subject to human oversight, ethical principles, and institutional accountability. The emphasis therefore shifts from technology adoption toward comprehensive institutional transformation.

Table 1 presents a comparative overview of the key characteristics distinguishing smart universities, AI-enabled universities, and AI-Native universities. The comparison highlights that the proposed framework extends beyond existing approaches by positioning AI as a core strategic capability that shapes institutional design, governance, and value creation. This transition from functional AI adoption to institution-wide AI integration constitutes the central conceptual contribution of the present study and provides the foundation for the framework developed in the following sections.

Table 1. Distinguishing Smart, AI-Enabled, and AI-Native Universities

Dimension	Smart University	AI-Enabled University	AI-Native University
Primary Focus	Infrastructure Intelligence	AI Adoption	Institutional Transformation
AI Usage	Selective	Functional	Institution-wide
Governance	Limited	Emerging	Core Capability
Teaching	Technology-Supported	AI-Assisted	AI-Integrated
Learning	Analytics-Supported	Personalized AI	AI-Orchestrated
Assessment	Traditional	AI-Assisted	AI-Resilient
Research	Digital Support	AI Tools	AI-Augmented Ecosystem
Human-AI Collaboration	Limited	Moderate	Foundational Principle
Strategic Role of AI	Optional	Important	Foundational Institutional Capability

The defining characteristic of an AI-Native University is that AI becomes embedded within institutional design, governance, and value creation processes rather than being deployed primarily as a collection of functional applications.

To the best of the author's knowledge, this is the first study to propose an integrated conceptual framework for the AI-Native University that combines operational domains, enabling layers, institutional governance, maturity pathways, readiness assessment, and human–AI collaboration within a unified higher education model.

4. Research Methodology

This study adopts a conceptual framework development methodology, appropriate for emerging phenomena where theoretical integration is needed before large-scale empirical validation (Jabareen, 2009; Gilson and Goldberg, 2015). A structured narrative review approach was employed to identify, synthesize, and integrate literature across multiple domains relevant to AI-enabled higher education, including Artificial Intelligence in Education (AIEd), learning analytics, educational data mining, digital transformation, smart universities, responsible AI, and higher education governance. The aim is not to test causal hypotheses, but to consolidate fragmented knowledge into a coherent explanatory and strategic framework capable of guiding future research and institutional transformation. Literature was identified primarily through searches of Scopus, Web of Science, ERIC, Google Scholar, and major publisher databases, focusing on studies related to AI in higher education, digital transformation, learning analytics, and AI governance published between 2010 and 2026.

Search queries combined the terms (“AI-Native university” OR “AI-enabled university” OR “smart university” OR “digital transformation”) AND (“higher education” OR “universit*”) AND (“artificial intelligence” OR “generative AI” OR “learning analytics” OR “AI governance”), restricted to peer-reviewed journal articles, books, and major institutional or policy reports published in English. An initial search yielded approximately 410 records across the five databases. After removing duplicates (n = 96) and screening titles and abstracts for relevance to institution-level AI adoption in higher education (excluding studies focused solely on K-12 contexts, single-tool technical evaluations, or non-educational organizational settings), 187 records were retained for full-text review. Of these, 132 sources met the inclusion criteria of addressing AI adoption, digital transformation, learning analytics, or governance at the institutional or systemic level and were retained for thematic synthesis; the remainder were excluded for insufficient institutional relevance or thematic overlap with already-represented sources. This screening procedure, while not a full systematic review, follows a transparent screening process consistent with narrative review methodology underpinning conceptual framework development (Jabareen, 2009).

4.1 Framework Development Process

The framework was developed in four stages.

1. **Literature identification:** Relevant scholarship was identified across major academic domains related to AIEd, learning analytics, educational data mining, digital transformation, smart universities, responsible AI, and higher education governance.
2. **Thematic synthesis:** The literature was reviewed to identify recurrent institutional functions, implementation conditions, opportunities, and risks associated with AI adoption in universities.
3. **Conceptual integration:** Themes were integrated primarily through socio-technical systems theory, digital transformation theory, and human-AI collaboration theory, while responsible AI and governance scholarship provided normative guidance for framework design.
4. **Framework refinement:** The model was refined through internal consistency checks, coverage of identified gaps, and alignment with practical institutional concerns reported in the literature.

This paper is a **conceptual contribution**. Its value lies in theory building, integrative synthesis, and framework articulation rather than empirical generalization. Future work should validate and refine the framework through case studies, Delphi panels, surveys, and longitudinal institutional analysis.

4.2 Theoretical Foundations

The framework is primarily grounded in three complementary theoretical perspectives and further informed by responsible AI and governance scholarship.

- Socio-technical systems theory emphasizes that technologies and organizations co-shape one another; successful transformation requires alignment between technical systems, human actors, work processes, and institutional values (Baxter and Sommerville, 2011).
- Digital transformation theory highlights strategic, structural, and cultural adaptation rather than narrow technology implementation (Vial, 2019).
- Human-AI collaboration theory frames AI as augmentative, emphasizing complementarity between human judgment and machine capability rather than substitution (Luckin, 2018; Dellermann et al., 2019)

The relationship between framework components and underlying theoretical foundations is further summarized in Appendix B.

4.3 Research Gap Matrix

To systematically position the proposed AI-Native University framework within the existing body of knowledge, a research gap matrix was developed. The matrix synthesizes major streams of scholarship relevant to AI adoption in higher education and identifies their principal contributions and limitations. Although prior research has generated valuable insights into intelligent tutoring systems, learning analytics, educational data mining, generative AI, digital transformation, smart universities, and responsible AI, these perspectives have largely evolved in parallel. Consequently, the literature remains fragmented and lacks an integrative framework capable of connecting teaching, learning, assessment, research, governance, and institutional strategy within a single conceptual model. Table 2 summarizes the key gaps identified through the literature synthesis and demonstrates how the proposed AI-Native University framework addresses these limitations.

Table 2. Research Gap Matrix

Research area	Major contribution in prior literature	Main limitation	Gap addressed by this paper
Intelligent tutoring systems	Personalized learner support	Focused on course or learner level	Extends personalization to institution-wide AI-enabled learning ecosystems
Learning analytics	Student monitoring and prediction	Often weakly integrated with governance and strategy	Embeds analytics within governance-enabled institutional architecture

Educational data mining	Pattern discovery and predictive modeling	Technology-centric orientation	Repositions data intelligence within human-AI institutional collaboration
Generative AI in education	Classroom support, content generation, feedback	Tool-level and short-term framing	Provides an institution-level transformation model
Digital transformation	Organizational modernization via digital systems	Developed largely before GenAI	Introduces AI-Native redesign logic
Smart universities	Intelligent campus infrastructure and operations	Limited pedagogical and assessment integration	Unifies academic and administrative domains
AI ethics/ governance	Principles for responsible AI	Often not higher-education specific	Develops a higher education-centered governance architecture

The literature synthesis and theoretical analysis collectively indicate the need for an integrated model capable of explaining institution-wide AI transformation in higher education. Figure 1 presents the conceptual research model underlying this study. The model illustrates how the identified research gaps and theoretical foundations inform the development of the AI-Native University (AINU) Framework and how the framework is expected to contribute to educational, organizational, and institutional outcomes.

4.4 Research Model for AI-Native University Development

Figure 1 presents the conceptual research model developed from the literature synthesis and theoretical foundations. The model illustrates how identified limitations in existing scholarship and insights from relevant theories collectively inform the development of the AI-Native University framework. It also highlights the institutional outcomes expected from successful AI-Native transformation.

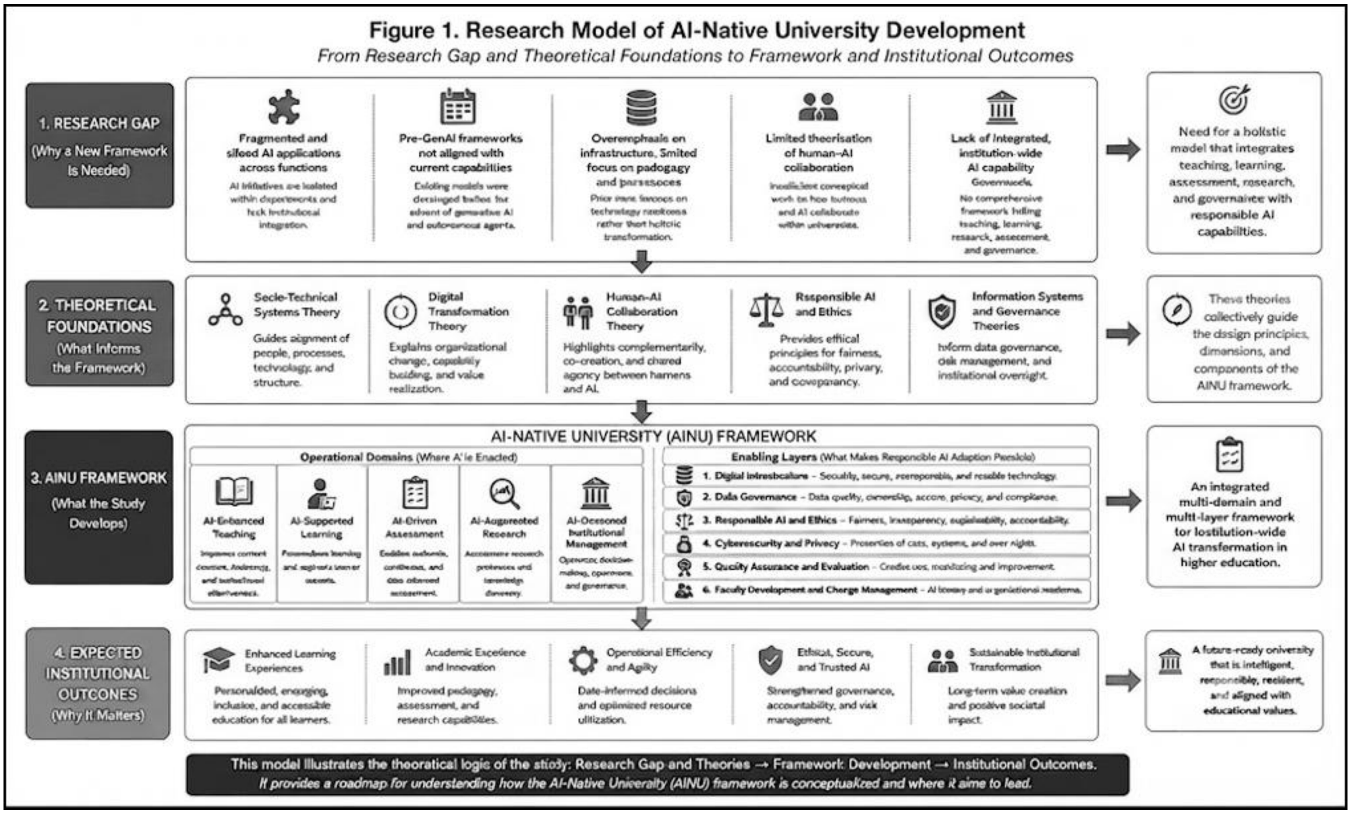

Figure 1. Research Model of AI-Native University Development
From Research Gap and Theoretical Foundations to Framework and Institutional Outcomes

Guided by the conceptual logic presented in Figure 1, the following section introduces the AI-Native University Framework and describes its major components, operational domains, and enabling layers.

5. The AI-Native University Framework

The **AI-Native University (AINU)** is defined as a higher education institution in which AI is embedded across core academic and administrative functions as a foundational capability, while human oversight, ethics, governance, and educational values remain central.

5.1 Core Premise

The AINU framework departs from conventional educational technology models in three ways.

First, it assumes **AI pervasiveness** across the institutional lifecycle rather than isolated deployment.

Second, it emphasizes **human-AI collaboration** rather than automation alone.

Third, it treats **governance and enabling conditions** as intrinsic design features, not afterthoughts.

5.2 Framework Architecture

In the context of this study, AI agents refer to intelligent software entities capable of performing autonomous or semi-autonomous tasks such as content generation, tutoring, advising, workflow support, data analysis, decision assistance, and knowledge retrieval. AI agents may include conversational systems, large language model assistants, recommendation engines, intelligent tutoring systems, and future autonomous educational agents operating within institutional environments.

The term *AI agents* is used broadly in this study to encompass both contemporary AI assistants (e.g., large language model–based conversational systems and intelligent tutoring assistants) and emerging autonomous agentic systems capable of planning, reasoning, coordinating complex educational workflows, and interacting with users or other AI systems. This broad definition reflects the rapidly evolving nature of AI technologies and ensures that the proposed framework remains applicable as higher education transitions from AI-assisted to increasingly agentic institutional environments.

Recent advances in agentic AI suggest that intelligent agents may increasingly perform semi-autonomous and autonomous functions across organizational environments, including workflow coordination, knowledge retrieval, decision support, research assistance, and personalized interaction (Wang et al., 2024; Xi et al., 2024). Within the AI-Native University framework, AI agents are conceptualized not merely as software tools but as emerging institutional actors that may increasingly participate in teaching, learning, research, and administrative processes. Through collaboration with students, faculty, and administrators, such systems have the potential to enhance learning experiences, support research activities, and improve organizational effectiveness while remaining subject to human oversight and institutional governance.

The framework comprises three nested layers:

1. **Core actor layer:** students, faculty, and AI agents.
2. **Operational layer:** five institutional domains where AI is enacted.
3. **Enabling layer:** institutional capabilities that make responsible AI adoption viable.

These layers collectively explain how AI-enabled transformation emerges through interactions among institutional actors, operational activities, and enabling conditions.

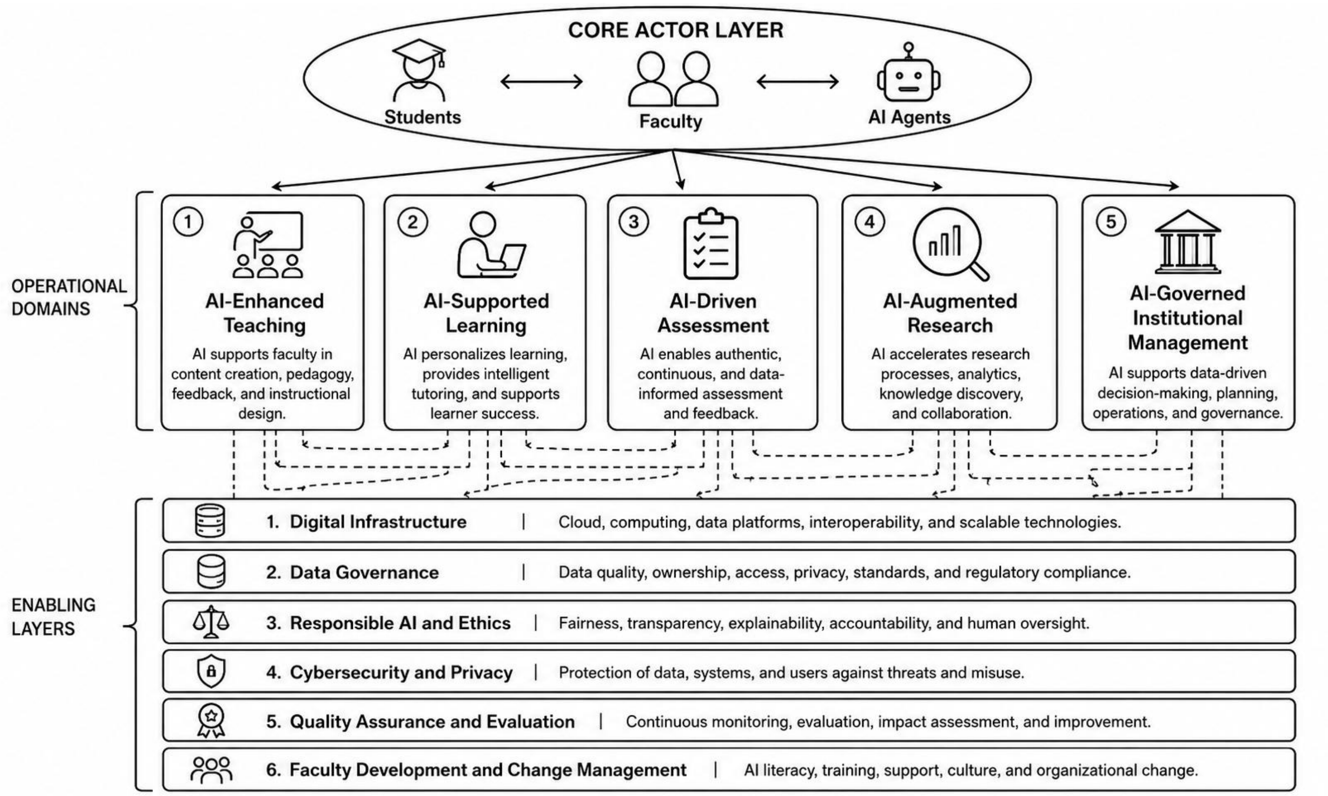

Figure 2. AI-Native University Conceptual Framework

Figure 2 illustrates that at the center are **students, faculty, and AI agents** as interacting actors. These actors operate across five institutional domains: teaching, learning, assessment, research, and institutional management. All domains are supported by enabling layers that ensure infrastructural, ethical, legal, organizational, and quality conditions for responsible implementation.

The framework should be interpreted as a dynamic and interconnected system rather than a collection of independent components. Changes within one operational domain may influence outcomes in other domains, while the enabling layers provide the institutional conditions necessary for sustainable and responsible AI integration. For example, advances in AI-driven assessment may affect teaching practices, learning behaviors, and governance requirements, illustrating the systemic nature of AI-Native transformation. Consequently, successful implementation requires coordinated development across academic, technological, organizational, and policy dimensions.

6. Operational Domains of the AI-Native University

6.1 AI-Enhanced Teaching

Teaching is transformed when AI supports content preparation, instructional design, feedback generation, learner differentiation, and routine communication. Faculty can use AI to generate examples, case studies, quizzes, lesson plans, multilingual content, and scaffolded explanations, thereby reducing repetitive workload and increasing time available for mentoring and higher-order pedagogical work (Luckin et al., 2016; Kasneci et al., 2023).

AI can also support **instructional decision-making** by aligning learning outcomes, prior student performance, and engagement data to recommend pacing, sequencing, and intervention strategies. However, the model assumes that faculty retain authority over curricular judgment, disciplinary interpretation, and the cultivation of critical thinking and ethical reasoning. AI enhances teaching; it does not replace the educator's epistemic and relational role (Selwyn, 2019; Holmes et al., 2019).

6.2 AI-Supported Learning

AI-supported learning refers to learner-centered personalization enabled by adaptive systems, conversational tutors, recommendation engines, and predictive support mechanisms. In the AINU model, AI helps create individualized pathways by analyzing engagement patterns, errors, pace, and demonstrated competencies to provide targeted resources and formative feedback (Ifenthaler and Yau, 2020; Strielkowski et al., 2025).

Modern intelligent tutoring systems and language-based assistants can explain concepts, generate practice tasks, offer hints, and support metacognitive reflection (Luckin et al., 2016; Strielkowski et al., 2025). When linked to student success systems, AI can identify at-risk learners and trigger early interventions. Yet this domain must be governed carefully to avoid intrusive surveillance, opaque profiling, or deterministic classification of students (Prinsloo and Slade, 2017; Holmes et al., 2022).

6.3 AI-Driven Assessment

Assessment is one of the most disrupted areas in the GenAI era because conventional take-home essays, problem sets, and coding tasks may no longer reliably reveal independent student capability. The AINU framework therefore conceptualizes assessment as shifting from output-only evaluation toward **authentic, continuous, and process-aware assessment** (Bearman et al., 2023; Perkins et al., 2023; Corbin et al., 2025; Mozelius et al., 2024).

AI can support assessment design through item generation, difficulty calibration, rubric alignment, and rapid feedback. It can also facilitate continuous evidence collection through portfolios, competency tracking, simulation performance, and reflective artifacts. In this model, AI does not simply automate grading; it helps redesign assessment toward higher-order thinking, situated problem solving, oral defense, iterative drafting, and collaborative inquiry. Human oversight remains essential to fairness, validity, and integrity.

6.4 AI-Augmented Research

Research is increasingly shaped by AI tools that assist with literature discovery, synthesis, coding, statistical support, transcription, knowledge mapping, and scientific writing assistance (Adjei et al., 2022; Nature, 2023). In the AINU framework, AI-augmented research includes support for identifying gaps, generating hypotheses, exploring trends, simulating scenarios, and improving administrative aspects of grant and project management.

At the same time, this domain introduces acute concerns regarding authorship, attribution, fabricated citations, reproducibility, and the opacity of AI-generated analytical suggestions. Universities therefore require clear policies on disclosure, verification, data provenance, and human accountability for research outputs (Else, 2023; UNESCO, 2023).

6.5 AI-Governed Institutional Management

Beyond academic functions, AI has growing relevance for institutional management. Universities can use AI for enrollment forecasting, applicant support, timetabling, resource allocation, curriculum demand analysis, student retention, quality assurance, and strategic planning (Daniel, 2015; OECD, 2021). In the AINU model, these systems form a layer of **predictive and decision-support governance** rather than automated managerial replacement.

The key distinction is that AI-governed management should remain **human-accountable governance** supported by analytics, not algorithmic rule by opaque systems. Institutional leaders remain responsible for final decisions, policy interpretation, and trade-offs involving equity, mission, and academic values.

7. Enabling Layers

The operational domains depend on enabling conditions that make AI adoption institutionally viable, lawful, and educationally legitimate.

7.1 Digital Infrastructure

AI-Native Universities require cloud-capable architectures, interoperable platforms, robust networks, secure storage, API-enabled ecosystems, and scalable compute capacity. Without reliable infrastructure, AI applications remain experimental and fragmented (OECD, 2021; García-Peñalvo, F. J. 2024).

7.2 Data Governance

Since AI systems depend on extensive data flows, universities need clear policies on data quality, ownership, access rights, lifecycle management, retention, interoperability, and compliance. Data governance is especially important where student behavior, assessment evidence, and institutional decision systems are linked (Prinsloo and Slade, 2017; Jones, 2019).

7.3 Responsible AI and Ethics

Responsible AI requires fairness, transparency, explainability, accountability, and human oversight (Floridi and Cowls, 2019; Jobin et al., 2019; OECD, 2019). In universities, this means ensuring that AI supports educational values, protects vulnerable groups, and remains open to audit and contestation. The growing adoption of AI in higher education also requires alignment with emerging international governance frameworks. Recent initiatives such as the European Union Artificial Intelligence Act, the NIST AI Risk Management Framework, and UNESCO's AI Competency Framework for Teachers emphasize transparency, accountability, human oversight, risk management, and responsible deployment of AI systems. These developments suggest that AI governance should evolve from a compliance-oriented activity into a strategic institutional capability that supports trust, legitimacy, and sustainable innovation.

7.4 Cybersecurity and Privacy

AI adoption enlarges the institutional attack surface. Risks include data breaches, prompt injection, identity misuse, model manipulation, and unauthorized extraction of sensitive content. Universities therefore need integrated privacy and cybersecurity controls aligned with AI procurement and deployment (ENISA, 2023; UNESCO, 2023).

7.5 Quality Assurance and Evaluation

AI systems should be subject to ongoing evaluation for accuracy, bias, pedagogical impact, reliability, and alignment with institutional policy. Quality assurance must extend beyond technical performance to include educational validity and student outcomes.

7.6 Faculty Development and Change Management

Institutional transformation depends on people, not tools alone. Faculty need AI literacy, assessment redesign capability, prompt and workflow skills, ethical awareness, and opportunities for experimentation within supportive governance structures (Kutty et al., 2024; Mhlanga, 2023; García-Peñalvo, F. J. 2024). Change management is needed to address resistance, workload concerns, and evolving professional identities.

8. Institutional Readiness and Maturity Model

The transition to AI-Native operations is evolutionary rather than instantaneous. A maturity model can help institutions benchmark progress and sequence investment. The readiness assessment checklist presented in Appendix A may serve as a starting point for the development of validated institutional AI readiness instruments.

8.1 Five Levels of Maturity

The transformation toward an AI-Native University is unlikely to occur through a single technological initiative or institutional policy. Rather, it is a gradual process that involves the development of technological capabilities, governance structures, organizational culture, faculty competencies, and strategic leadership. Similar to digital transformation journeys observed in other sectors, universities are expected to progress through a series of maturity stages as they move from initial experimentation with AI technologies toward institution-wide integration and optimization.

The proposed maturity model provides a conceptual framework for understanding this progression. It recognizes that institutions differ significantly in terms of resources, infrastructure, regulatory environments, and readiness for change. Consequently, the model should not be interpreted as a rigid sequence of predetermined steps, but rather as a developmental pathway that can assist institutional leaders in assessing current capabilities, identifying strategic priorities, and planning future investments. The five maturity levels reflect increasing degrees of AI adoption, governance maturity, cross-functional integration, and organizational transformation.

Table 3. Illustrative Indicators for AI-Native University Maturity Levels

Level	**Example Indicator**
Awareness	Less than 10% of faculty and administrative units actively using AI tools; limited governance structures
Adoption	10–30% adoption through pilot projects and departmental initiatives
Integration	30–60% adoption with cross-functional integration and formal institutional policies
Optimization	60–80% adoption supported by workflow redesign, analytics, and continuous improvement
AI-Native Transformation	More than 80% institution-wide adoption with AI embedded in academic and administrative operations

Illustrative thresholds for conceptual purposes only.

The indicators presented in Table 3 are illustrative rather than prescriptive. Their purpose is to demonstrate how institutions might operationalize the maturity model for assessment, benchmarking, and strategic planning purposes. The percentage ranges are illustrative and intended to demonstrate possible operationalization; future empirical studies should refine and validate these thresholds. Actual thresholds may vary according to institutional size, mission, disciplinary profile, regulatory requirements, technological infrastructure, and available resources. Furthermore, progression between maturity levels should not be viewed solely in terms of technology adoption. Sustainable advancement also depends on the development of governance mechanisms, faculty capabilities, responsible AI practices, organizational culture, and leadership commitment. Future empirical research should refine and validate these indicators through survey-based measurement, expert evaluation, and cross-institutional comparative studies.

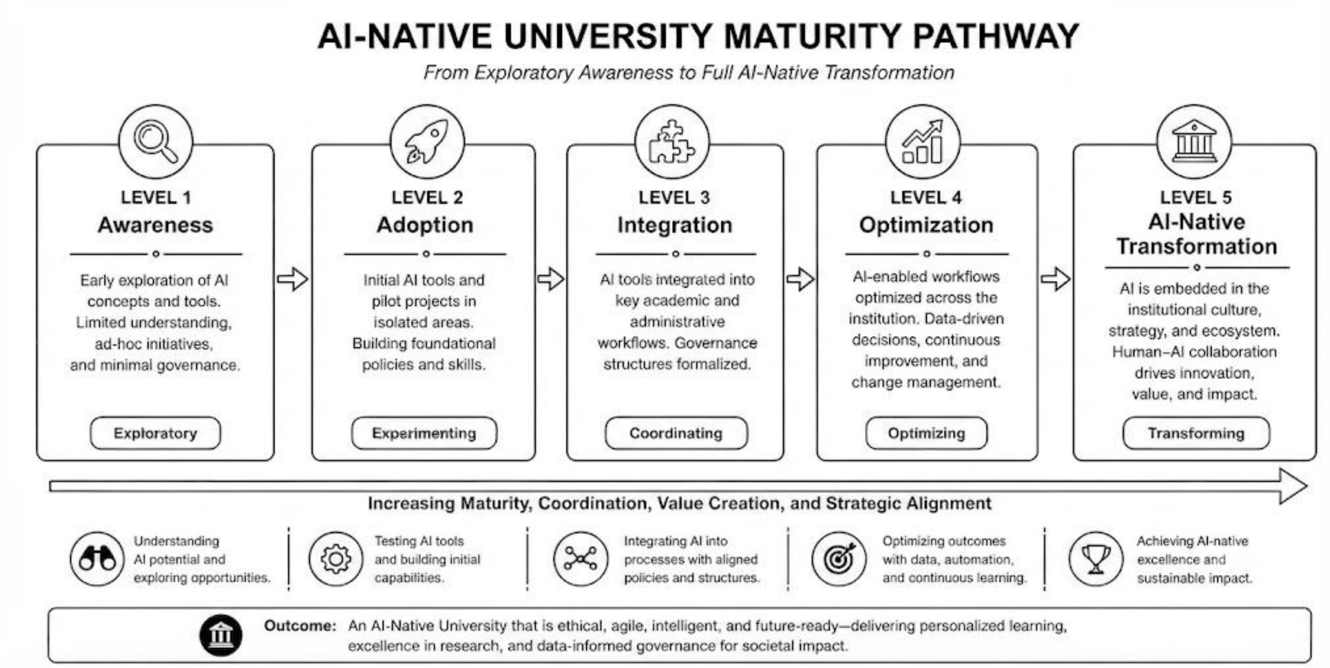

Figure 3. AI-Native University Maturity Pathway

Figure 3 illustrates how institutions progress from exploratory awareness to full AI-Native transformation through increasingly coordinated implementation, governance maturation, workflow integration, and strategic alignment.

8.2 Implementation Roadmap

The transition toward an AI-Native University requires a structured implementation approach that balances innovation with governance, risk management, and organizational readiness. Although implementation pathways will vary across institutions, the following roadmap provides a general sequence of activities that can guide strategic planning and institutional transformation efforts:

1. Establish an institutional AI strategy aligned with mission, pedagogy, and governance.
2. Audit current capabilities across infrastructure, data, policy, faculty readiness, and risk exposure.
3. Launch targeted pilot projects in priority domains such as teaching support, advising, or assessment redesign.
4. Create governance mechanisms including ethics review, procurement standards, privacy controls, and accountability structures.
5. Scale successful use cases through interoperable platforms and staff development.
6. Continuously evaluate impact using educational, operational, and ethical performance indicators.

9. Challenges and Risks

Although the AINU model offers strategic value, it also introduces substantial risks.

9.1 Academic Integrity and Authentic Learning

Generative AI undermines assumptions underlying traditional assessment forms. Universities must redesign assessment toward authentic demonstrations of learning rather than relying on detection-based responses alone (Bearman et al., 2023; Perkins et al., 2023).

9.2 Bias and Fairness

AI models may reproduce historical and representational bias in admission, advising, language support, and assessment. Institutions need fairness auditing, representative testing, and mechanisms for appeal and review (Floridi and Cowls, 2019; Holmes et al., 2022).

9.3 Privacy, Surveillance, and Datafication

The expansion of analytics and AI may intensify student surveillance and normalize high-granularity data extraction. This raises concerns about autonomy, consent, and power asymmetries in educational environments (Prinsloo and Slade, 2017; Williamson, 2017).

9.4 Faculty Resistance and Cultural Tension

Academic staff may perceive AI as a threat to autonomy, expertise, or workload balance. Successful transformation requires participatory design, transparency, support, and shared governance rather than top-down imposition (Selwyn, 2019; Kutty et al., 2024).

9.5 Technological Dependency and Vendor Lock-In

Heavy reliance on proprietary models and platforms can create strategic dependency, cost escalation, and limited institutional control over data, model updates, and compliance. Procurement and interoperability therefore become governance issues, not merely IT concerns.

9.6 Epistemic and Ethical Concerns

AI systems may alter how knowledge is produced, trusted, and attributed within the university. If poorly governed, they may weaken critical inquiry, obscure accountability, or incentivize superficial efficiency over meaningful learning.

10. Policy and Practice Implications

The transition toward AI-Native Universities has implications that extend beyond technology adoption. Successful implementation requires coordinated changes in leadership, governance, faculty roles, student competencies, quality assurance mechanisms, and public policy. The proposed framework highlights that AI transformation is not solely a technical challenge but also an organizational, pedagogical, and strategic undertaking. Consequently, universities, accreditation agencies, and policymakers must work collaboratively to ensure that AI adoption enhances educational quality, promotes responsible innovation, and supports equitable institutional development.

10.1 Implications for University Leadership

University leaders should move from ad hoc experimentation toward institution-level AI strategies integrating pedagogy, governance, infrastructure, and risk management. Leadership commitment is essential for aligning innovation with educational values.

10.2 Implications for Faculty

Faculty roles will increasingly include learning design, critical facilitation, ethical oversight, and orchestration of human-AI collaboration. Professional development should focus on assessment redesign, disciplinary uses of AI, responsible classroom integration, and the effective adoption of generative AI within teaching and learning practices (García-Peñalvo, F. J. 2024). AI literacy is increasingly recognized as a foundational competency for both students and educators. Beyond technical proficiency, AI literacy encompasses the ability to understand AI capabilities and limitations, critically evaluate AI-generated outputs, make informed ethical decisions, and collaborate effectively with intelligent systems (Long and Magerko, 2020; Ng et al., 2021; Ranieri et al., 2025). Consequently, AI-Native Universities must treat AI literacy as a core graduate attribute and a strategic faculty development priority.

10.3 Implications for Students

Students require more than technical familiarity with AI tools. They need **AI literacy**, **data literacy**, **critical evaluation skills**, and the ability to collaborate with AI while maintaining intellectual accountability (Long and Magerko, 2020; Ng et al., 2021; UNESCO, 2023). Universities should therefore embed AI literacy, ethical AI use, critical evaluation of AI outputs, and responsible human-AI collaboration within graduate attributes and curriculum frameworks.

10.4 Implications for Quality Assurance and Accreditation

Accreditation bodies should update quality frameworks to include AI governance, assessment integrity, transparency, data use, and human oversight. Existing quality assurance models may not fully capture AI-mediated educational environments.

10.5 Implications for Governments and Policymakers

Public policy should support equitable infrastructure, regulatory clarity, research funding, ethical standards, and capacity development for institutions with uneven readiness. Without policy support, AI may widen inequalities between institutions and systems.

Taken together, these implications suggest that the successful development of AI-Native Universities depends on alignment among institutional strategy, human capacity development, governance frameworks, and supportive public policy. Institutions that approach AI as a strategic capability rather than a collection of isolated technologies are more likely to realize sustainable benefits while maintaining educational integrity, accountability, and public trust.

10.6 Limitations of the Study

Several limitations should be acknowledged when interpreting the proposed AI-Native University (AINU) framework.

- First, this study is conceptual in nature and does not include empirical data collection or statistical validation. The framework has been developed through the synthesis and integration of existing literature and theoretical perspectives, and therefore requires empirical testing to establish its reliability, validity, and practical applicability.
- Second, although a framework validation strategy has been proposed, the current study does not include expert evaluation, survey-based assessment, or case study evidence. Consequently, the relationships among the proposed framework components and maturity dimensions remain theoretically derived and should be interpreted as propositions for future investigation rather than empirically confirmed findings.
- Third, the framework is specifically designed for higher education institutions. While some concepts may be applicable to other educational settings or knowledge-intensive organizations, the model was developed within the context of universities and may require adaptation before being applied to schools, vocational institutions, corporate learning environments, or public-sector organizations.
- Fourth, the implementation of AI within higher education is influenced by significant contextual factors, including national regulations, institutional missions, resource availability, technological infrastructure, cultural expectations, and levels of digital maturity. As a result, the pathways through which institutions progress toward AI-Native transformation may differ considerably across countries and regions.
- The framework has not yet been evaluated across universities with different institutional missions, geographical contexts, or regulatory environments.
- Finally, the field of artificial intelligence is evolving rapidly. Advances in generative AI, multimodal systems, autonomous agents, and emerging governance frameworks may alter institutional practices and priorities over time. Consequently, the proposed framework should be viewed as an evolving conceptual model that will require periodic refinement as AI technologies, educational practices, and regulatory environments continue to develop.

Despite these limitations, the study provides a useful foundation for understanding institution-wide AI transformation and offers a starting point for future empirical research, validation studies, and policy development in higher education.

11. Future Research Agenda

The AINU model is best understood as a platform for further empirical inquiry.

11.1 Framework Validation Strategy

As a conceptual framework, the AI-Native University (AINU) model requires empirical validation to assess its completeness, relevance, and practical applicability across diverse higher education contexts. Future research should therefore adopt a multi-method validation approach.

- First, a Delphi study involving 20–30 experts from the fields of Artificial Intelligence in Education (AIEd), higher education management, educational technology, learning analytics, and AI governance could be conducted to evaluate the framework's conceptual clarity, comprehensiveness, and practical relevance. Multiple rounds of expert review would help refine framework components and establish consensus regarding the critical dimensions of an AI-Native University.
- Second, survey-based validation may be employed to examine the relationships among the proposed framework components. Data collected from university leaders, faculty members, instructional designers, and technology administrators could be used to assess institutional readiness, perceived importance of framework dimensions, and the applicability of the maturity model across different institutional settings.
- Third, case study validation involving universities at different stages of AI adoption would provide insights into how the framework operates in practice. Comparative case studies could examine institutions ranging from early-stage adopters to highly AI-integrated universities, enabling researchers to identify implementation patterns, contextual influences, success factors, and barriers to transformation.

Together, these validation approaches would strengthen the theoretical robustness of the AINU framework and support its evolution into a practical tool for institutional assessment, strategic planning, and policy development in higher education.

11.2 AI Readiness Measurement

Researchers can develop and validate instruments for measuring infrastructure maturity, governance capability, faculty readiness, assessment redesign capacity, and student AI literacy.

11.3 Longitudinal Transformation Studies

Longitudinal work is needed to understand how universities evolve across maturity stages and which conditions enable or hinder sustainable adoption.

11.4 Comparative Governance Models

Future studies should compare centralized, federated, and hybrid governance models for AI in higher education.

11.5 Human-AI Boundary Design

Research should identify which tasks should remain primarily human-led, which can be AI-supported, and how accountability should be distributed across these arrangements.

11.6 AI-Native Curriculum and Assessment

Additional work is needed on curriculum architectures, competency frameworks, pedagogical models, and assessment approaches designed explicitly for AI-rich educational environments (García-Peñalvo, F. J. 2024).

11.7 Theoretical Propositions

To facilitate future empirical testing and theory development, the conceptual framework gives rise to several research propositions. These propositions are intended to guide future quantitative, qualitative, and mixed-method investigations examining the relationships among institutional AI capabilities, governance mechanisms, human-AI collaboration, and educational outcomes.

The following theoretical propositions are offered for future empirical testing.

P1: Institutional AI integration positively influences organizational adaptability.

P2: Faculty AI readiness moderates educational effectiveness.

P3: AI governance maturity positively influences institutional trust.

P4: Human-AI collaboration positively affects learning outcomes.

P5: Institutional AI maturity predicts transformation success.

P6: Assessment redesign mediates the relationship between AI adoption and academic integrity.

P7: Student AI literacy positively influences learning outcomes in AI-supported environments.

P8: Responsible AI governance positively influences institutional trust and sustainability.

11.8 Theoretical Contributions

This study contributes to the emerging literature on artificial intelligence in higher education by advancing a conceptual framework that moves beyond technology adoption toward institution-wide transformation. The proposed AI-Native University (AINU) framework extends existing scholarship in four important ways.

Contribution 1: AI-Native University as a New Institutional Archetype

The primary contribution of this study is the introduction of the AI-Native University as a distinct institutional archetype for higher education. Existing literature has examined digital universities, smart universities, and AI-enabled universities; however, these models typically conceptualize artificial intelligence as a supporting technology or a collection of functional applications. In contrast, the AI-Native University positions AI as a foundational institutional capability embedded across teaching, learning, assessment, research, administration, and governance. This conceptualization shifts the focus from isolated AI adoption toward institution-wide transformation and provides a new lens for understanding how universities may evolve in the age of generative AI.

Contribution 2: Extension of Digital Transformation Theory into Generative AI Environments

The study extends digital transformation theory by examining how organizational transformation occurs when artificial intelligence increasingly participates in institutional processes rather than merely a supporting technology. Traditional digital transformation frameworks were largely developed in contexts characterized by digitization, automation, and data analytics. The emergence of generative AI introduces fundamentally different capabilities, including content generation, reasoning support, decision assistance, and autonomous task execution. By integrating these capabilities into a higher education context, the proposed framework expands digital transformation theory and highlights the need for new models that account for human-AI interaction, institutional adaptation, and AI-enabled value creation.

Contribution 3: Advancement of Institutional-Level Human-AI Collaboration Theory

Existing human-AI collaboration research has primarily focused on individual tasks, workplace productivity, decision support systems, and human-computer interaction. This study extends the discussion to the institutional level by conceptualizing universities as socio-technical ecosystems in which faculty, students, administrators, and AI agents interact continuously. The framework proposes that successful AI-Native transformation depends not on replacing human expertise, but on developing effective forms of collaboration that leverage the complementary strengths of humans and intelligent systems. In doing so, the study contributes to an emerging understanding of how human-AI collaboration can be designed, governed, and sustained within complex educational organizations.

Contribution 4: Development of an AI Maturity Framework for Higher Education

A further contribution is the introduction of a structured maturity perspective for understanding institutional AI transformation. While maturity models have been widely applied in digital transformation, capability development, and information systems research, relatively few frameworks address the progressive evolution of AI capabilities within higher education institutions. The proposed five-level maturity pathway—Awareness, Adoption, Integration, Optimization, and AI-Native transformation—provides a conceptual foundation for assessing institutional progress and identifying developmental priorities.

Collectively, these contributions advance theoretical understanding of AI-enabled institutional transformation and establish a foundation for future empirical research, comparative studies, and policy development in higher education. By positioning artificial intelligence as a strategic organizational capability rather than merely a technological tool, the study offers a new perspective on how universities may adapt, innovate, and create value in an increasingly AI-driven educational landscape.

Table 4. Summary of Theoretical Contributions

Contribution	Existing Literature	AINU Contribution
Institutional Model	AI as tool	AI as institutional capability
Digital Transformation	Pre-GenAI focus	AI-Native institutional transformation

Human-AI Collaboration	Task-level	Institution-level
Maturity Assessment	Limited HE focus	Dedicated AI maturity pathway

Table 4 summarizes the main theoretical contributions of this study and shows how the AI-Native University framework builds on and extends existing research. Together, these contributions present AI as a core institutional capability, highlight the importance of human–AI collaboration at the university level, and provide a foundation for future research and institutional transformation in higher education.

12. Conclusion

Higher education is entering an era in which artificial intelligence is evolving from a supporting technology into a strategic institutional capability. Advances in generative AI, learning analytics, intelligent tutoring systems, and AI-assisted decision-making are transforming teaching, learning, research, administration, and governance across universities (e.g., Strielkowski et al., 2025). At the same time, institutions face significant challenges related to ethics, transparency, accountability, academic integrity, and human oversight. Despite increasing AI adoption, many universities continue to implement AI through fragmented initiatives rather than coherent institution-wide strategies.

This paper introduced the concept of the **AI-Native University (AINU)** as a new institutional model for understanding and guiding AI integration across higher education. Drawing on Artificial Intelligence in Education, digital transformation, socio-technical systems theory, and human–AI collaboration, the study developed a conceptual framework comprising five operational domains supported by six enabling layers for responsible and sustainable AI adoption.

The central premise of the AI-Native University is that AI should be viewed not merely as a technological tool but as a strategic institutional capability. Rather than replacing human expertise, AI should augment teaching, learning, research, and decision-making through human-centered, ethically governed, and purpose-driven collaboration. Achieving this vision requires universities to redesign governance, assessment, faculty development, data management, and organizational practices while ensuring that AI remains aligned with educational values and societal needs.

The study contributes to the literature by identifying limitations in existing approaches to AI adoption, conceptualizing AI as an institution-wide capability, defining the core dimensions of AI-Native Universities, and proposing a maturity pathway to guide institutional transformation. The framework also provides a foundation for future empirical validation, institutional benchmarking, and policy development.

Ultimately, the AI-Native University represents not simply a technological destination but a strategic vision for the future of higher education. As AI continues to evolve, the key challenge for universities will be to integrate it responsibly, effectively, and ethically in ways that enhance educational quality, institutional resilience, public trust, and societal impact.

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71. Appendices
72. Appendix A. AI-Native University Readiness Assessment Checklist
73. Appendix A presents an illustrative readiness assessment checklist designed to help higher education institutions evaluate their preparedness for AI-Native transformation. The checklist covers key dimensions of institutional readiness, including infrastructure, governance, ethics, cybersecurity, faculty development, assessment, research, and leadership. It is intended as a preliminary diagnostic instrument that can support institutional self-assessment, strategic planning, and future development of a standardized AI-Native University Readiness Index.
74. Appendix B. Mapping of Framework Components to Theoretical Foundations

75. Appendix B illustrates how the major components of the AI-Native University framework are grounded in the theoretical perspectives adopted in this study. By linking operational domains and enabling layers to socio-technical systems theory, digital transformation theory, and human-AI collaboration theory, the appendix provides additional transparency regarding the conceptual foundations of the framework and demonstrates the theoretical logic underlying its development.
76. Appendix C. Evolution Journey Toward the AI-Native University
77. Figure A1 illustrates the evolutionary pathway through which higher education institutions may progress from traditional operating models toward AI-Native transformation. The figure highlights key developmental stages, characteristic features, enabling conditions, and expected outcomes associated with each phase of institutional evolution. It serves as a conceptual roadmap for understanding the long-term trajectory of AI integration in higher education.