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Governing the Ungoverned: Institutional Leadership and Organizational Ambidexterity in the AI Adoption of Universities

A Systematic Review with Thematic Synthesis

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Abstract. The rapid integration of artificial intelligence into higher education has produced a significant imbalance: a growing body of research addresses AI tools and their effects on student learning, while the institutional and leadership dimensions of AI governance remain systematically underexplored. This systematic review with thematic synthesis (PRISMA 2020) examines how indexed literature conceptualizes AI governance and leadership in higher education institutions (HEIs), what institutional and managerial factors operate as facilitators or barriers, what structural tensions characterize the field, and what the Latin American context reveals about the limits of prevailing frameworks. Drawing on a corpus of 30 verified sources — 20 peer-reviewed studies (2021–2026) plus 10 foundational theoretical works included by exception — the analysis identifies five analytical themes: fragmented governance architectures without systemic accountability; the underresearched role of academic leadership as the critical institutional link; the theoretical limits of individual acceptance models (TAM/UTAUT) when applied to organizational-level decisions; datafication as covert governance operating beneath formal policy layers; and Latin America's near-absence from indexed production as a structural finding rather than a methodological limitation. The study proposes an integrative conceptual framework articulating organizational ambidexterity (O'Reilly & Tushman, 2004, 2013), dynamic capabilities (Teece, 2007), and the critique of datafication (Williamson, 2018; Selwyn & Gasevic, 2020) as a unified analytical device for AI governance in HEIs, anchored in the specific conditions of Latin American higher education.

Keywords: Artificial Intelligence Governance; Higher Education Institutions; Organizational Ambidexterity; Dynamic Capabilities; Datafication

1. Introduction

The publication of ChatGPT in November 2022 did not inaugurate the presence of artificial intelligence in higher education, but it irreversibly altered the terms in which that presence had to be thought. What until that moment was primarily a technical field became overnight a problem of institutional management, university policy, and academic leadership. University authorities worldwide found themselves needing to make urgent decisions about technologies they had not requested, that their students were already using, and that no existing regulatory framework adequately governed (Crompton & Burke, 2023; Bond et al., 2024). The speed of that transition was itself an organizational finding: for the first time in decades, technological transformation outpaced institutional capacity to process it.

The academic response was equally accelerated. Scientific production on AI in higher education doubled or tripled each year between 2021 and 2024 compared to preceding years (Crompton & Burke, 2023), and China displaced the United States as the country with the highest publication volume (Zawacki-Richter et al., 2019). However, that growth was deeply asymmetric. Systematic reviews reveal that the bulk of indexed production originates from the Global North, while Latin America, Southeast Asia, sub-Saharan Africa, and much of Eastern Europe remain underrepresented in high-impact venues (Salas-Pilco & Yang, 2022; Bond et al., 2024). This asymmetry is not trivial: it means that the conceptual frameworks, adoption models, and policy recommendations dominating the field have been built on institutional conditions that are not universal.

Beyond geographic distribution, the field exhibits a thematic gap identified convergently by its most rigorous reviews. Zawacki-Richter et al. (2019) documented that research concentrated on tool optimization and the student as user, relegating to a marginal plane both teachers and management teams as units of analysis. Crompton and Burke (2023) verified empirically that only 11% of studies incorporated administrators or institutional managers as research objects. Bond et al. (2024), in the first meta-systematic review of the field, reached the same conclusion: the governance and leadership dimension of AI adoption is the most persistent and least attended gap in indexed literature.

Against this backdrop, this systematic review proposes three articulated contributions. The first is empirical: to synthesize and critically analyze the indexed literature on AI governance and leadership in HEIs through a rigorous PRISMA 2020 systematic review with thematic synthesis — to the best of the author's knowledge, the first systematic review to apply an integrative organizational framework explicitly to the institutional governance of AI in higher education. The second is theoretical: to propose an integrative conceptual framework bringing into dialogue organizational ambidexterity (O'Reilly & Tushman, 2004, 2013), dynamic capabilities (Teece, 2007), and the critique of datafication (Williamson, 2018; Selwyn & Gasevic, 2020). The third is regional: to anchor that framework in the specific conditions of Latin American higher education, incorporating heterogeneity as a constitutive variable rather than a residual.

2. Theoretical Framework

The phenomenon this study examines involves three dimensions that no existing theoretical tradition integrates satisfactorily: an organizational dimension — how institutions decide, structure themselves, and lead in contexts of accelerated technological transformation; a strategic dimension — what capabilities distinguish institutions that govern AI well from those that adopt reactively; and a normative dimension — what values, power relations, and distributive consequences the incorporation of algorithmic systems produces in institutions whose mandate includes equity, critical formation, and public accountability.

2.1. Why Technology Acceptance Models Are Insufficient

TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003) have dominated empirical research on technology adoption in higher education for more than three decades. Their explanatory strength at the individual user level is well documented; so is their limitation. They were built to explain individual user behavior toward a tool. The question this study poses — how higher education institutions govern AI adoption — is of a different scale and requires a different class of theory. A university deciding to incorporate a learning analytics system, regulate generative AI use in assessments, or establish an institutional data ethics committee is not making a user decision: it is exercising institutional authority over a technology with implications for its students, faculty, academic processes, and public accountability. No combination of structural equation betas on use intention captures that decision.

2.2. Organizational Ambidexterity and Dynamic Capabilities

March (1991) identified as constitutive of all organizational learning the tension between exploration of new possibilities and exploitation of established certainties. O'Reilly and Tushman (2004, 2013) converted this tension into a solvable organizational design problem: their ambidextrous organization does not seek balance between exploration and exploitation but their structured coexistence, integrated at the level of the senior management team. Applied to AI governance in HEIs, organizational ambidexterity illuminates a problem the literature has treated as a binary dilemma when it is actually an organizational design problem. The exploitation pole includes what the institution must preserve: formative process quality, assessment authenticity, student data rights, and equity commitments. The exploration pole includes informed experimentation with AI tools and adaptive governance policies. O'Reilly and Tushman (2013) distinguish between structural and contextual ambidexterity; Latin American universities with limited resources favor the latter.

Teece's (2007) dynamic capabilities complement ambidexterity by providing the vocabulary of processes through which this architecture is built and sustained: sensing — identifying opportunities and threats before they crystallize; seizing — translating detected opportunities into institutional decisions and governance structures; and transforming — modifying processes, structures, and organizational culture when previous responses no longer suffice. O'Reilly and Tushman (2008) explicitly established that organizational ambidexterity is, in Teece's language, a higher-order dynamic capability: precisely the one that allows organizations to explore and exploit simultaneously.

2.3. The Critique of Datafication: The Normative Dimension

A framework built exclusively on ambidexterity and dynamic capabilities describes the strategic management problem with precision but asks no questions about whether the direction of that management is ethically admissible. Williamson (2018) documented that the data infrastructure sustaining the contemporary university operates through metrics, rankings, platforms, and analytics systems that redistribute decision-making power toward technical and commercial actors with interests that do not necessarily coincide with those of the institution or its students. Selwyn and Gasevic (2020) extend this diagnosis: analytics systems that treat the non-quantifiable as irrelevant produce an impoverished image of learning used as the basis for institutional decisions with real consequences.

Incorporating the datafication critique into the framework means sustaining three questions that institutional governance must answer honestly before each adoption decision: Who is harmed? (requiring identification of the distributive effects of the system, especially on the most vulnerable groups); Who decides? (requiring visibility into the power architecture each AI system incorporates, including commercial provider interests); and What cannot be datafied? (requiring identification of values and practices constitutive of the educational mission that cannot be reduced to metrics without losing what makes them valuable).

3. Methodology

3.1. Study Design

This study adopts a systematic review with thematic synthesis design (Thomas & Harden, 2008), reported in accordance with the PRISMA 2020 statement (Page et al., 2021). The choice is grounded in three considerations: (1) the field presents marked epistemological heterogeneity, making quantitative meta-analysis unfeasible; (2) thematic synthesis allows derivation of higher-order analytical contributions, methodologically appropriate when the objective is proposing an emergent conceptual framework; (3) the PRISMA protocol offers the greatest defensibility in peer review by making search, selection, and analysis procedures explicit and reproducible. The protocol was pre-registered on OSF prior to search execution (doi: https://doi.org/10.17605/OSF.IO/CU28Q).

3.2. Research Questions

The study is oriented by four pre-formulated research questions: (RQ1) How does indexed literature published between 2021 and 2026 conceptualize AI governance and leadership at the institutional level in HEIs? (RQ2) What institutional and managerial factors are identified as facilitators or barriers for AI adoption in universities? (RQ3) What theoretical and practical tensions exist between the efficiency logic underlying technology adoption models and the critical perspective on datafication? (RQ4) What presence does the Latin American context have in indexed venues on this topic, and what knowledge gaps does that presence or absence reveal?

3.3. Eligibility Criteria

Inclusion and exclusion criteria were operationalized from an adapted PICO framework (Liberati et al., 2009) before executing the searches. Table 1 presents the complete set of criteria.

Table 1. Eligibility criteria operationalized for the systematic review

Dimension / Criterion	Operationalization
INCLUSION CRITERIA	
Type of source	Peer-reviewed articles published in journals indexed in Scopus, Web of Science Core Collection, or ERIC; systematic reviews, empirical studies, and conceptual/theoretical studies with structured argumentation.
Period	2021–2026 (publication or epub ahead of print). By exception, foundational works prior to 2021 constitutive of the conceptual framework (e.g., March, 1991; Teece, 2007; O'Reilly & Tushman, 2004, 2013; Williamson, 2018; Zawacki-Richter et al., 2019; Selwyn & Gasevic, 2020).
Thematic focus	Institutional, managerial, or governance dimension of AI adoption in HEIs. Studies focused on classroom-level AI use included only when they explicitly articulate implications for institutional management or policy.
Language	English, Spanish, or Portuguese.
Context	HEIs of any country or region; studies from the Global South and Latin America actively sought.
EXCLUSION CRITERIA	
Educational level	Studies focused exclusively on K-12 education without reference to HE.
Publication type	Editorials, letters to the editor, unsupported opinion pieces, conference proceedings without formal peer review, technical reports without verifiable DOI.
Indexing	Publications in non-indexed journals or with predatory indicators.
Duplicates	The definitive published version is retained; preprints excluded if the final article is available.
Grey literature	Institutional reports, unpublished preprints, policy documents: cited as context in Introduction and Discussion but excluded from the coded PRISMA corpus.
Exclusively technical focus	Algorithm engineering or computational performance studies without reference to the educational or institutional dimension.

Note. HEI = higher education institution. Grey literature cited in the manuscript body as context but excluded from the PRISMA-coded corpus.

3.4. Information Sources and Search Strategy

The systematic search was executed in three primary databases: Scopus, Web of Science Core Collection (WoS), and ERIC. Search reporting follows the PRISMA-S extension (Rethlefsen et al., 2021). All database searches were executed in June 2026. The search was supplemented by forward citation tracking from the three most-cited reviews (Zawacki-Richter et al., 2019; Bond et al., 2024; Crompton & Burke, 2023) and backward citation searching of reference lists. Table 2 presents the complete search strings.

Table 2. Search strings by database

Database	Search string
Scopus	TITLE-ABS-KEY(("artificial intelligence" OR "generative AI" OR "GenAI" OR "large language model*" OR "ChatGPT" OR "learning analytics") AND ("higher education" OR universit* OR "tertiary education") AND (governance OR leadership OR "institutional adoption" OR "organizational change" OR management OR policy OR strateg* OR "decision-making")) AND PUBYEAR > 2020
Web of Science	TS=(("artificial intelligence" OR "generative AI" OR "GenAI" OR "ChatGPT" OR "learning analytics") AND ("higher education" OR universit*) AND (governance OR leadership OR "institutional adoption" OR "organizational change" OR policy OR strateg*)) AND LA=(English OR Spanish OR Portuguese) AND PY=(2021-2026)
ERIC	Thesaurus descriptors: "Artificial Intelligence" AND ("College Administration" OR "Educational Policy" OR "Educational Administration") AND "Higher Education". Supplemented with free-text: ("AI governance" OR "AI leadership" OR "institutional AI adoption").

Note. The symbol * is truncation. Language and year restrictions vary according to each database's interface.

Figure 1 presents the PRISMA 2020 flow diagram documenting the complete selection process, from database identification through final inclusion.

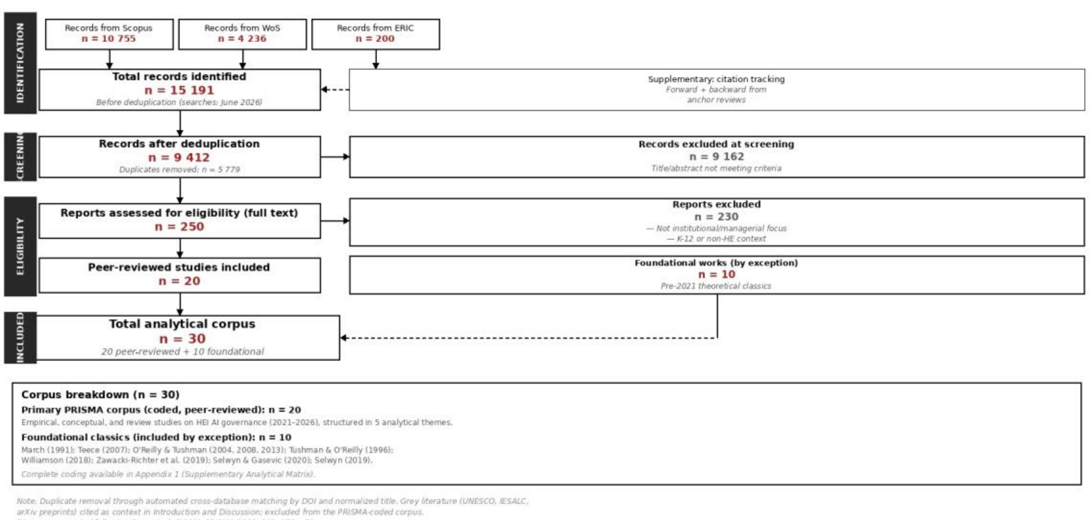

Figure 1. PRISMA 2020 flow diagram of the study selection process

Note. PRISMA = Preferred Reporting Items for Systematic Reviews and Meta-Analyses (Page et al., 2021). Duplicate removal was performed through automated cross-database matching by DOI and normalized title. Complete coding of all 30 corpus entries is described in Appendix 1 and deposited in the OSF repository (https://osf.io/yk2s8/).

3.5. Study Selection

Retrieved records were exported in RIS and consolidated into a single dataset. Duplicates were removed through automated cross-database matching by DOI and normalized title (n = 5,779 duplicates removed), yielding 9,412 unique records screened by title and abstract. Of these, 250 were assessed in full text for eligibility. The review was conducted by a single researcher, which constitutes a deviation from the PRISMA recommendation of dual independent screening at the full-text eligibility stage. To mitigate this risk, two safeguards were implemented: (a) internal consistency was audited on 20% of Phase 1 records (title and abstract screening), with no disagreements identified in the audited subset; and (b) all uncertain cases at the full-text stage were resolved through discussion with a second academic reviewer. While these measures reduce the probability of systematic selection error, they do not fully substitute for independent dual coding of the entire eligibility phase, and this remains a recognized methodological limitation (see Section 7).

3.6. Data Extraction

Data from each included study were extracted using a structured analytical matrix, described in Appendix 1 and deposited in the OSF repository (https://osf.io/yk2s8/), with fields for: authors, year, country or region, journal and quartile, study objective, methodological design, sample or corpus, main results, author-declared limitations, contribution to the field, and assigned thematic pillar. The matrix was piloted on five studies selected to cover variation in study type, region, and pillar, and adjusted after that pilot.

3.7. Quality Assessment

Study quality was assessed using a rubric adapted from the Mixed Methods Appraisal Tool (MMAT, version 2018; Hong et al., 2018), extended to incorporate conceptual and theoretical studies, using a three-value scale (0 = absent, 1 = partial, 2 = complete). Table 3 presents the rubric.

Table 3. Quality appraisal rubric (adapted from MMAT 2018)

Dimension	Key indicators evaluated	Score (0–2)
1. Clarity of objective	The research question or objective is clearly stated and coherent with the title and abstract.	0 / 1 / 2
2. Design adequacy	The methodological design is appropriate for answering the stated objective.	0 / 1 / 2
3. Analytical rigor	Data collection, analysis, or synthesis procedures are sufficiently described to be reproducible or auditable.	0 / 1 / 2

Dimension	Key indicators evaluated	Score (0–2)
4. Methodological transparency	Limitations, epistemological assumptions, and potential biases are honestly reported.	0 / 1 / 2
5. Conclusion soundness	Conclusions are grounded in the data or argument presented; they do not exceed what the design can support.	0 / 1 / 2
TOTAL SCORE	**Sum of five dimensions. Maximum: 10. Studies scoring ≥6 are deemed acceptable quality.**	**0–10; ≥6 = ok**

Note. Maximum score: 10. Studies scoring ≥6 are considered acceptable quality. Adapted from Hong et al. (2018). Low-scoring studies are not automatically excluded; the score modulates the interpretive weight assigned to each finding.

3.8. Synthesis Method

The analytical method was thematic synthesis (Thomas & Harden, 2008), operating in three progressive stages (Table 4). The integrative conceptual framework presented in the Discussion emerges as an analytical interpretation in Stage 3, derived from patterns observed in descriptive themes — not as a prior assumption of the design.

Table 4. Stages of thematic synthesis (Thomas & Harden, 2008)

Stage	Procedure	Analytical product
Stage 1: Line-by-line coding	Integral reading of each study. Identification of textual findings preserving authors' original language. Assignment of inductive labels (codes) without prior categories.	*Code map per study (~300–500 initial codes)*
Stage 2: Descriptive themes	Systematic grouping and comparison of emergent codes. Identification of convergences, divergences, and cross-cutting patterns.	*Nine descriptive themes*
Stage 3: Analytical themes	Interpretation of descriptive themes to derive higher-order analytical contributions. The integrative framework emerges as a plausible explanation of observed patterns.	*Integrative conceptual framework: ambidexterity + dynamic capabilities + datafication critique*

Note. The integrative conceptual framework emerges in Stage 3 as analytical interpretation, not as a prior assumption of the design.

4. Results

4.1. Selection Process and Corpus Characteristics

The systematic search executed in Scopus (n = 10,755), Web of Science Core Collection (n = 4,236), and ERIC (n = 200) yielded 15,191 total records before deduplication. After removing 5,779 duplicates, 9,412 unique records were screened by title and abstract. Of these, 250 were assessed in full text, and 20 peer-reviewed studies met all inclusion requirements. Additionally, 10 foundational theoretical works published prior to 2021 were included by exception (March, 1991; Teece, 2007; O'Reilly & Tushman, 2004, 2008, 2013; Tushman & O'Reilly, 1996; Williamson, 2018; Zawacki-Richter et al., 2019; Selwyn & Gasevic, 2020; Selwyn, 2019), yielding a total analytical corpus of 30 sources. The complete selection process is documented in Figure 1 (PRISMA 2020 flow diagram).

Three characteristics of the corpus warrant mention. First, temporal concentration: more than two-thirds of the peer-reviewed corpus was published between 2023 and 2026. Second, geographic concentration: most of the corpus originates from the Global North, with Latin American and Caribbean production representing only approximately 10% — not an artifact of the search process but a structural finding developed as Analytical Theme 5. Third, methodological heterogeneity: the corpus combines systematic reviews, quantitative and qualitative empirical studies, and theoretical essays, which precludes quantitative synthesis but legitimizes thematic synthesis. Table 5 presents the corpus distribution.

Table 5. Characteristics of the analytical corpus (n = 30)

Category	Distribution	n / %
Foundational classics (pre-2021)	March (1991); Tushman & O'Reilly (1996); O'Reilly & Tushman (2004, 2008, 2013); Teece (2007); Williamson (2018); Selwyn (2019); Zawacki-Richter et al. (2019); Selwyn & Gasevic (2020)	10 / 33.3%
2021–2022	Post-pandemic expansion; pre-ChatGPT period	4 / 13.3%
2023–2024	GenAI explosion; first post-ChatGPT systematic reviews and governance-oriented studies	9 / 30.0%
2025–2026	Consolidation; emergence of governance frameworks and institutional policy studies	7 / 23.3%
Global North (USA, UK, Australia, Western Europe)	Dominant production; centered on anglophone and high-capacity institutional contexts	14 / 46.7%
Asia (China, South Korea, India)	Accelerated growth in AI-in-education research and technology adoption studies	5 / 16.7%
Latin America and the Caribbean	Sparse indexed production; regional evidence concentrated in a small number of studies	3 / 10.0%
International / supranational	Comparative, multinational, or supranational studies and frameworks	8 / 26.7%
Systematic review / meta-review / scoping review	Includes systematic, meta-systematic, and scoping reviews of AI in HE literature	8 / 26.7%
Conceptual / theoretical / critical essay	Theoretical frameworks, critical essays, and conceptual analyses of AI governance	12 / 40.0%
Quantitative empirical (survey / SEM / PLS)	Survey-based studies using SEM, PLS, or regression on adoption determinants	5 / 16.7%
Qualitative empirical / mixed methods	Interview, case study, or mixed methods designs exploring institutional AI governance	5 / 16.7%

Note. Quartile classifications verified individually against the Scimago Journal Rank (SJR) information (2024 edition). Grey literature cited as institutional context and excluded from the coded synthesis corpus.

4.2. Thematic Synthesis: Five Analytical Themes

Inductive analysis through thematic synthesis produced nine descriptive pillars in Stage 2. Their aggregation and interpretation in Stage 3 derived five higher-order analytical themes, presented in Table 6 and developed in the following subsections.

Table 6. Five analytical themes emerging from the thematic synthesis

No.	Analytical theme	Core finding	Pillars
T1	Governance without government: institutional architecture of AI in HEIs	Governance frameworks exist but are fragmentary, not systemic. Adoptive pressure exceeds institutional deliberative capacity.	A, G, H
T2	The managerial link: disposition, competence, and legitimate resistance	Academic leadership is the most determinant and least researched institutional factor. Faculty resistance is a signal of the limits of adoption models.	B, C, D
T3	Technology adoption as organizational change: the limits of TAM/UTAUT	Individual adoption determinants do not scale to the institutional level without theoretical mediation. Ethical determinants are the emerging frontier.	C, D, E
T4	Datafication as covert governance	AI systems reconfigure who decides and through what mechanisms. AI governance is also data policy.	F, H
T5	Latin America: the gap as finding, not deficit	Scarcity of indexed Latin American literature is structural evidence of a research capacity gap and urgent need for a regional agenda.	I

Note. The 'Pillars' column refers to the thematic pillars of the Analytical Matrix (A–I), available in Appendix 1.

Theme 1: Governance Without Government. The first analytical theme emerges from a paradox traversing the entire Pillar A corpus: HEIs have responded to generative AI's irruption with a proliferation of policy instruments — acceptable use policies, ethics committees, academic integrity guidelines — that do not configure governance systems but reactive and fragmentary responses to immediate pressures. An et al. (2025), analyzing generative AI guidelines issued by the top 50 U.S. universities, found that 94% had faculty-facing guidelines predominantly addressing academic integrity and authorized tools, leaving data governance, accountability, and equity largely unaddressed. This is consistent with what Williamson (2018) called the 'hidden architecture' of the smart university: issuing an acceptable use policy for ChatGPT is not AI governance — it is regulating a visible surface while the data infrastructure sustaining it remains unquestioned.

Theme 2: The Managerial Link. Academic leadership is simultaneously the most determinant institutional factor for AI adoption and the most neglected research object. Crompton and Burke (2023) quantified this neglect: only 11% of studies incorporated administrators or institutional managers as research objects. Bond et al. (2024) confirmed this group was the most systematically absent from secondary production. A central finding in the corpus is that of all measured variables, the variable with the greatest explanatory weight on managerial disposition to adopt AI responsibly was ethical consideration. At the managerial level, ethical awareness appears to act as a sensing capacity in Teece's (2007) sense rather than as a barrier to adoption. Qualitative evidence on faculty resistance published in 2025 demonstrates that resistance to generative AI does not distribute according to TAM/UTAUT predictor variables but according to identity, ethical, and value dimensions: this resistance is not dysfunctional — it is a signal that the adoption process is being managed without value negotiation.

Theme 3: Technology Adoption as Organizational Change. Pillar C contains the highest density of quantitative empirical studies, all measuring individual use intention as the dependent variable. These are valid findings for their level of analysis. The problem emerges when the same framework is extended to explain institutional adoption decisions. Alzahrani et al. (2022) documented that learning analytics adoption challenges in HEIs are systemic — forming dependency networks in which none can be resolved in isolation — and that their solution requires intervention at the organizational culture level, not just individual training. A university reconfiguring its information architecture and assuming responsibilities over student data is making an institutional decision, not a user decision.

Theme 4: Datafication as Covert Governance. When a university adopts AI systems that process data about its students and its own functioning, it is not simply improving operational efficiency: it is delegating decision-making to algorithmic architectures whose logic is frequently opaque to the institutional actors who are supposed to govern. Selwyn and Gasevic (2020) add the equity dimension: datafication does not operate on a uniform field but on pre-existing inequalities it tends to reproduce and amplify. Predictive student dropout systems have shown systematic biases penalizing first-generation students and members of historically underrepresented groups — exactly the groups that HEI inclusion policies aim to favor.

Theme 5: Latin America — The Gap as Finding. The fifth analytical theme emerges not from the content of available Latin American studies but from their structural scarcity. Pillar I contains only a small set of references with explicit regional anchoring, and very few are original empirical studies with the region's own data. Interpreting this gap as a mere lag would be methodologically naive and politically questionable. The conditions in which Latin American higher education operates — precarious financing structures, high institutional heterogeneity, traditions of university autonomy, constitutional mandates for inclusion and free access — produce specific governance problems requiring their own analytical frameworks.

4.3. Structural Tensions of the Field

Beyond the five analytical themes, the synthesis reveals five structural tensions traversing the entire corpus that no single available theoretical tradition resolves satisfactorily in isolation (Table 7). These tensions are the material on which the integrative framework presented in the Discussion is built.

Table 7. Structural tensions identified in the corpus (transversal synthesis)

Tension	Description	Status in the literature
Efficiency vs. Equity	AI is presented as an optimization tool; simultaneously, evidence shows it amplifies digital divides without explicit governance.	*Not resolved: requires institutional value choices, not merely technical improvement.*
Individual adoption vs. Institutional governance	TAM/UTAUT models explain individual use decisions; institutional adoption implies distinct organizational, political, and cultural dynamics.	*Nascent governance frameworks (SHEILA, UPDF-GAI) attempt to bridge this gap but have not been longitudinally validated.*
Global framework vs. Regional context	Supranational frameworks assume regulatory and institutional conditions that do not hold in lower-capacity contexts.	*Adaptation is a condition of pertinence, not weakness.*
Dysfunctional vs. Legitimate resistance	Adoption literature treats faculty resistance as a barrier. Recent qualitative evidence shows it is frequently a rational response to ethical and identity uncertainties.	*Reframing resistance as an institutional signal is a methodological contribution with direct practical implications.*
Algorithmic transparency vs. Technical complexity	Governance frameworks demand AI explicability; the technical complexity of large language models makes that explicability partial or illusory.	*AI governance cannot be limited to technical auditing: it requires deliberation on values and responsibilities.*

Note. The 'Status in the literature' column reflects the synthesis of included studies, not a normative position of this study.

5. Discussion

5.1. From Corpus to Framework: Integration as Theoretical Necessity

The five analytical themes share a characteristic that cannot be overlooked: none of them can be explained satisfactorily from a single theoretical tradition. Fragmented governance (Theme 1) is not a design failure that technology adoption literature can diagnose, because that literature lacks categories to distinguish between an acceptable use policy and a governance system. Legitimate resistance (Theme 2) is not statistical noise that TAM/UTAUT can absorb. Covert datafication (Theme 4) is not an externality that organizational ambidexterity corrects alone, because without an explicit normative limit a university can be perfectly ambidextrous in exploiting and exploring student surveillance. The Latin American gap (Theme 5) is evidence that frameworks produced in the Global North have not found the conditions to become relevant in the region. This observation leads not to theoretical skepticism but to integration. Table 8 synthesizes the integrative framework.

Table 8. Integrative conceptual framework: components, traditions, and functions

Framework component	Theoretical tradition	Function in the framework	Tensions addressed
Exploration/ exploitation engine	Organizational ambidexterity (March, 1991; O'Reilly & Tushman, 2004, 2013)	Explains how HEIs can maintain academic integrity (exploit) while experimenting with AI (explore) through structures integrated by senior leadership.	Efficiency vs. Equity; Adoption vs. Governance
Sensing, seizing, and transforming capabilities	Dynamic capabilities (Teece, 2007)	Provides operational language: what a leadership that governs AI well does concretely — senses opportunities and threats, seizes them institutionally, reconfigures structures and culture.	Readiness gap; Resistance as signal; Leadership competencies
Normative limit of governance	Datafication critique (Williamson, 2018; Selwyn & Gasevic, 2020)	Prevents framework from drifting into techno-optimism. Demands three questions: Who is harmed? Who decides? What cannot be datafied?	Transparency vs. Complexity; Covert governance; Equity implications
Latin American contextual anchoring	Regional diagnosis (Salas-Pilco & Yang, 2022; UNESCO IESALC, 2024)	Situates framework under conditions of institutional heterogeneity, research capacity gaps, and asymmetric dependency on Global North AI providers. Heterogeneity is a constitutive variable.	Global framework vs. Regional context; Latin American gap as finding

Note. The framework does not resolve the tensions identified in Table 7 but articulates them analytically. The resolution of each tension depends on institutional decisions that theory can orient but not substitute.

5.2. Organizational Ambidexterity as Governance Architecture

Applying organizational ambidexterity to AI governance in HEIs illuminates a problem the literature has tended to treat as a binary dilemma when it is actually an organizational design problem. Empirical evidence on academic leadership disposition suggests that integration between exploration and exploitation operates not only through structure but also through managerial culture: leaders who best govern AI simultaneously sustain openness to experimentation and clarity about which values are non-negotiable. The institutional readiness gap can be reinterpreted as a problem of incomplete ambidexterity: institutions responding only from the exploitation pole sacrifice exploration; those responding only from exploration sacrifice exploitation and fundamental institutional commitments.

5.3. Dynamic Capabilities as Operational Language for Leadership

Teece's (2007) dynamic capabilities provide the processes through which ambidextrous architecture is built and sustained. The sensing capacity implies the institutional ability to identify opportunities and threats before they crystallize into crises. Evidence that ethical sensitivity of university managers predicts responsible AI leadership suggests that ethical awareness is a form of anticipatory detection. The seizing capacity refers to translating detected opportunities into institutional decisions; the SHEILA framework (Tsai et al., 2018) represents an attempt to systematize this capacity. The transforming capacity is the most demanding: no study in the corpus documents genuine organizational reconfiguration in response to AI governance challenges, an absence that is itself a finding about the current state of institutional capabilities.

5.4. The Datafication Critique as the Framework's Normative Limit

A framework built solely on ambidexterity and dynamic capabilities risks becoming what it aims to prevent: a management technology optimizing adoption without interrogating its consequences. The datafication critique fulfills in the framework the function of normative limit, preventing the logic of institutional efficiency from colonizing the entire analysis. This means sustaining three questions before each adoption decision: Who is harmed? Who decides? What cannot be datafied?

5.5. The Latin American Anchoring: Heterogeneity as Constitutive Variable

The framework's Latin American anchoring modifies the theory based on conditions that reconfigure it substantively. Organizational ambidexterity presupposes the institution has sufficient resources to maintain simultaneously an exploitation and an exploration pole. In most Latin American HEIs, this condition does not hold, which forces incorporation of contextual ambidexterity — where exploration and exploitation coexist in the same actors and structures. Dependence on AI systems developed by Global North providers with training data not representing Latin American populations adds a technological sovereignty dimension that supranational frameworks address still insufficiently.

5.6. A Research Agenda: Six Priority Lines

The study's findings support a research agenda with six priority lines: (L1) AI governance in Latin American HEIs — empirical institutional studies on adoption and regulation decisions; (L2) Faculty resistance as organizational signal —

qualitative studies reframing resistance as institutional data; (L3) Organizational ambidexterity in HEIs — longitudinal empirical studies validating the framework across institutional types; (L4) Longitudinal impacts of AI governance on equity — cohort or panel studies estimating differential equity outcomes; (L5) Political economy of AI in Latin American HEIs — critical analysis of dependency relationships with commercial providers from the Global North; (L6) Governance maturity frameworks adapted to LatAm — development and validation of institutional AI governance maturity assessment instruments incorporating regional conditions.

5.7. Implications for Practice and Institutional Policy

For university leaders, the framework suggests AI governance is not a delegable technical function but a strategic function requiring senior management involvement as the integration mechanism between exploitation and exploration poles. For regional coordination bodies, the documented gap suggests inter-institutional cooperation is a structural necessity: no single Latin American university has individually the research mass, technical capacity, and resources to build a robust AI governance framework. For researchers, the central proposition — that HEIs with greater organizational ambidexterity and more developed dynamic capabilities produce better AI governance outcomes measured in equity, integrity, and adaptability — is empirically falsifiable through comparative or longitudinal designs.

6. Conclusion

This systematic review documented the mismatch between the urgency of AI governance as a university management problem and the state of indexed knowledge: approximately 89% of scientific production on AI in higher education concentrates on classroom and tool dimensions, while institutional governance, leadership, and policy remain the least developed and most needed. The five structural tensions identified are not passing contradictions of a young field — they are second-order problems that no available theoretical tradition resolves separately, and whose persistence justifies the integrative framework proposed here. That framework articulates organizational ambidexterity — conceived not as managerial virtue but as deliberate institutional architecture — as the device for understanding how a university can preserve what is valuable while building transformation capacity; dynamic capabilities as the operational vocabulary of institutional leadership; and the datafication critique as the normative limit preventing institutional optimization logic from colonizing what is, before all else, a process of value choices about the kind of university one wants to be.

Three propositions synthesize this study's contribution. First: institutional AI governance is not a delegable technical function but a strategic one defining the type of institution one aspires to be. Second: individual technology acceptance models are necessary but insufficient; organizational theory is needed — in ambidexterity, dynamic capabilities, and the datafication critique — though the educational technology field has not systematically incorporated it. Third: the Latin American gap in indexed production must be treated as the starting point for the region's own research agenda, not as confirmation that Global North frameworks need only be applied. What this work names with greatest precision is the task ahead: building the organizational theory of AI governance that university leaders need and that does not yet exist at the scale or with the regional pertinence the moment demands.

7. Limitations

Five limitations are declared. First, the screening and full-text eligibility assessment were conducted by a single researcher. Although internal consistency was audited on 20% of Phase 1 records and all uncertain full-text cases were discussed with a second academic reviewer, the study did not implement independent dual coding of the entire full-text eligibility phase, as recommended by the PRISMA standard for minimizing selection bias. This is the most significant methodological limitation of the review. Second, although the search explicitly included Spanish and Portuguese, indexed production on AI governance in HEIs in those languages proved extremely scarce, reflecting both a real production gap and a structural indexing bias favoring English. Third, the field of AI in HEIs is expanding so rapidly that some findings may become outdated between study completion and publication. Fourth, the proposed integrative framework is theoretical in nature: it articulates existing traditions and proposes hypotheses but does not provide primary empirical evidence of its functioning in real institutional contexts. Fifth, the corpus was deliberately focused on the institutional and managerial dimension, meaning the framework does not claim to explain the pedagogical dimension of adoption, only the organizational one.

8. Declarations

Ethics approval: Not applicable. This study is a systematic review of published literature and does not involve human subjects, clinical data, or primary data collection requiring ethical approval.

Availability of data and materials: The analytical matrix supporting the conclusions of this article is deposited in the Open Science Framework (OSF) at https://osf.io/yk2s8/. The pre-registered review protocol is available at https://doi.org/10.17605/OSF.IO/CU28Q. Appendix 1 describes the structure and fields of the matrix.

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Authors' contributions: The sole author — CRediT taxonomy: Conceptualization; Methodology; Formal analysis; Investigation; Data curation; Writing – original draft; Writing – review and editing; Visualization. The author read and approved the final manuscript.

Use of AI tools declaration: No AI-generated text has been included in this manuscript. During preparation, the author used Claude (Anthropic) exclusively for language refinement, structural editing, table formatting support, and reference-format checking. AI tools were not used to execute database searches, determine eligibility, extract data, perform quality appraisal, code studies, conduct the thematic synthesis, or formulate findings and conclusions. All methodological tasks were developed and validated by the human author. All references were individually verified against their original sources by the author.

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Type of English: This manuscript is written in American English throughout.

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Appendix 1

Analytical matrix description. The complete coding matrix covers all 30 corpus entries (20 peer-reviewed studies and 10 foundational theoretical works included by exception). The matrix includes the following fields: authors, year, country or region, journal and quartile (SJR 2024), study objective, methodological design, sample or corpus, main results, author-declared limitations, contribution to the field, and assigned thematic pillar (A–I).

The full analytical matrix is deposited as an open-access file in the Open Science Framework at https://osf.io/yk2s8/, ensuring long-term accessibility and reproducibility. The pre-registered review protocol is available at https://doi.org/10.17605/OSF.IO/CU28Q.