

Stakeholder Experiences of Artificial Intelligence in University Management at Two Chinese Universities in Hubei Province

Duan Zheng, Luh Putu Artini, Sariyasa, Putu Suarcaya

Educational Science, Postgraduate Program, Universitas Pendidikan Ganesha, Singaraja, Indonesia

Hubei Enshi College, Enshi, Hubei, China

duan@student.undiksha.ac.id

duanzheng666666@gmail.com

Language Education Doctoral Program, Graduate School, Universitas Pendidikan Ganesha, Singaraja, Indonesia

putu.artini@undiksha.ac.id

Master's Program in Computer Science, Graduate School, Universitas Pendidikan Ganesha, Singaraja, Indonesia

sariyasa@undiksha.ac.id

Applied Bachelor's Program in English for Business and Professional Communication, Faculty of Language and Arts, Universitas Pendidikan Ganesha, Singaraja, Indonesia

p.suarcaya@undiksha.ac.id

HOW TO CITE: ABSTRACT

Duan Zheng, Luh Putu Artini,
Sariyasa, Putu Suarcaya (2026).
Stakeholder Experiences of Artificial
Intelligence in University Management
at Two Chinese Universities in Hubei
Province.
International Journal of Special
Education, 41(24s), 1077 – 1106

Research on artificial intelligence (AI) in higher education has concentrated on teaching and learning, leaving the administrative core of the university comparatively under-examined. This study asks how AI technologies are experienced, applied, and governed within the management systems of two public universities in China, and how AI-generated data enters managerial decision-making. A qualitative phenomenological design was applied. Six analytical constructs, including AI infrastructural embeddedness, administrative process integration, perceived administrative efficiency, human readiness, AI governance assurance, and decision augmentation, were derived from an integrated theoretical framework combining systems theory, diffusion of innovation and the technology–organisation–environment framework, human capital and AI capability theory, institutional theory, and socio-material and human-centred AI perspectives. Four instruments were used, semi-structured interviews with 15 participants (five administrators, four IT staff, three faculty members, three students), two focus group discussions (n = 10), analysis of eight institutional documents, and six non-participant observation sessions. Data were analyzed through open coding,

category development, thematic synthesis, and interpretative phenomenological analysis, then triangulated across instruments. The findings showed that AI is experienced not as an innovation under trial but as normalized institutional infrastructure. Embedding is role-differentiated rather than uniform where administrators encounter AI through reporting and planning interfaces, IT staff through system architecture, faculty through learning analytics, and students through service platforms. Efficiency gains are consistently reported but bounded by interpretive rather than operational competence. Governance and privacy assurance operate as conditions of perceived value rather than as secondary compliance concerns. Across all participant groups, AI is positioned as advisory rather than autonomous. The two sites diverge consistently, University A integrates AI operationally, University B analytically, within a shared trajectory. The study specifies six theoretically grounded constructs, each with defined sub-dimensions, derivation, and operationalization, for research on AI in university management. It provides evidence of a later adoption stage than most of the literature describes and sets out a nomological network and measurement agenda for subsequent quantitative work.

COPYRIGHT STATEMENT:

Copyright: © 2026 Authors.
Open access publication under the
terms and conditions
of the Creative Commons Attribution
(CC BY)
license (<http://creativecommons.org/licenses/by/4.0/>).

Keywords: artificial intelligence; university management; higher education administration; institutional analytics; AI governance; digital transformation; phenomenology; China

Introduction

Artificial intelligence is no longer confined to the classroom (Crompton & Burke, 2023; George & Wooden, 2023). Universities now run smart campus platforms (Polin et al., 2023), predictive analytics dashboards (Daniel, 2015; Ifenthaler & Yau, 2020), automated scheduling and administrative systems (Chen et al., 2020; Kuleto et al., 2021), and conversational service systems (Okonkwo & Ade-Ibijola, 2021) to coordinate work that once relied on manual reporting, scattered spreadsheets, and face-to-face administrative contact. In a growing number of institutions, what began as experimentation with discrete tools has become an integrated management

infrastructure (George & Wooden, 2023; Polin et al., 2023). The literature has been quick to describe this shift as transformation (Katsamakos et al., 2024; George & Wooden, 2023). It has been slower to show what the transformation consists of, for whom, and under what conditions (Bates et al., 2020; Zawacki-Richter et al., 2019). The gap between the rhetoric of AI-enabled university management and the evidence base supporting it is the starting point of this study.

The imbalance is partly one of attention. Successive systematic reviews describe a field organised around instruction. Zawacki-Richter et al. (2019), synthesising 146 studies, found AI applications concentrated in profiling and

prediction, assessment, adaptive systems, and intelligent tutoring, with institutional and administrative uses forming a thin stratum. Crompton and Burke (2023) quantified the imbalance more sharply. Of 138 studies published between 2016 and 2022, 72% focused on students, 17% on instructors, and only 11% on managers, even as publication volume rose two- to threefold in 2021–2022. Bond et al. (2024), working at the level of review-of-reviews, note growth in admissions optimisation, retention prediction, and scheduling, yet still call for greater attention to ethics, collaboration, and methodological rigour. The convergence of these reviews is itself telling. Each documents the neglect of management, but none can characterise what management AI does once deployed, because the primary studies needed to support such a characterisation largely do not exist.

Where management applications have been examined, the evidence is thinner than its frequent citation suggests. Reported benefits cluster around three claims: automation of routine processing, faster institutional reporting, and better coordination across units (Chen et al., 2020; Kuleto et al., 2021). These claims are plausible, but they rest predominantly on institutional self-report, vendor-adjacent case descriptions, or analyses of system capability rather than observation of use. What a system can do and what an organisation does with it are different empirical questions, and the literature has tended to answer the first while presenting the answer as if it settled the second. Benefits that are projected become benefits that are reported, and benefits that are reported become benefits that are cited, without the intervening step of examining practice *in situ*.

Quantitative adoption research has been more rigorous but answers a narrower question than it is often taken to answer. Chatterjee and Bhattacharjee (2020), surveying 329 respondents in Indian universities, found that performance expectancy and effort expectancy predicted attitudes toward AI adoption, and that facilitating conditions such as institutional resources, training, and technical support exerted significant influence. Wang et al. (2021) reported compatible results among teaching staff. These studies establish that acceptance is conditional on organisational provision. Their limitations, however, are structural rather than incidental. They measure intention or attitude rather than the experience of established use, they rely on cross-sectional self-report, and they treat the institution as a homogeneous adopting unit whose members differ in degree but not in kind. The last assumption deserves scrutiny. An administrator reading a dashboard, an IT specialist maintaining a data pipeline, a lecturer interpreting an engagement indicator, and a student querying a chatbot are not positioned at different points on a single acceptance scale. They encounter the same institutional system from structurally different positions, with different stakes, different information, and different capacities to contest its outputs. Instruments that aggregate these positions into an institution-level score may be measuring an artefact of aggregation rather than a property of the institution.

A parallel body of work on institutional analytics complicates the transformation narrative further. Early contributions made a strong case that analytics could convert dispersed organisational data into actionable managerial knowledge (Long & Siemens, 2011; Daniel, 2015), and Ferguson (2012) traced the drivers and tensions of this movement in

education. The subsequent empirical record is more modest. Mahroeian and Daniel (2021) found analytics use in practice concentrated in operational monitoring rather than the strategic reorientation the earlier literature anticipated. Implementation research explains part of the shortfall. Drawing on complexity leadership theory, Tsai et al. (2019) identified strategic ambiguity, unevenly distributed capability, and unclear ownership as recurring obstacles to institution-wide adoption, and Gašević et al. (2019) proposed treating adoption as an organisational rather than technical undertaking. This work is directly relevant to management AI, since the underlying infrastructures are frequently identical. Yet it shares a limitation with the acceptance literature: it is largely concerned with why adoption stalls and says comparatively little about what happens in institutions where it does not.

Critical scholarship asks a different and sharper question: not whether these systems work, but what they do to the institutions that adopt them. Williamson and Eynon (2020) argue that digital systems in universities operate less as tools than as infrastructural arrangements, a largely invisible architecture of dashboards, standards, and data flows that reorganises institutional priorities as it operates. Selwyn (2019) contends that analytics alter the informational basis of educational governance by making continuous performance monitoring possible, and Pasquale's (2015) account of algorithmic opacity identifies the managerial consequence: decision-makers may act on outputs whose derivation they cannot inspect. These arguments are persuasive, but they are seldom tested against the accounts of people who operate the systems daily. The critical literature tends to infer institutional

effects from system design and policy discourse; the managerial literature tends to infer them from system capability. Neither has systematically asked staff and students how institutional AI is encountered. An older distinction offers a way to bridge the two. Zuboff (1988), studying early workplace computerisation, separated technology's capacity to *automate*, substituting machine for human effort, from its capacity to give information, generating new information that renders organisational activity visible. The distinction matters because the critical literature's concerns about monitoring and opacity attach mainly to information, while the managerial literature's claims about efficiency attach mainly to automating. Treating "AI in management" as a single phenomenon obscures the fact that its benefits and its risks may arise from different mechanisms.

The governance literature has expanded rapidly but remains weighted toward principle over practice. Floridi et al. (2018) argue that organisations embedding AI need explicit ethical frameworks governing data collection, analysis, and use. Jobin et al. (2019), surveying 84 global ethics documents, identify transparency, justice and fairness, non-maleficence, responsibility, and privacy as the most frequently invoked principles, and Cath et al. (2018) examine how such principles might translate into governance mechanisms. Education-specific frameworks have followed. Nguyen et al. (2023) derive seven principles for AI in education and, significantly, treat governance and stewardship as a first-order principle rather than an implementation detail; international guidance similarly foregrounds transparency, accountability, and human oversight (Molina-Carmona & García-Peñalvo, 2024). The difficulty is that a convergence of

principles is not evidence of their enactment. Institutional theory has long anticipated the possibility that formal structures are adopted for legitimacy while operational practice diverges (Meyer & Rowan, 1977), and nothing in the current literature establishes whether University AI governance is enacted in routine work, or whether it is visible to the people it is meant to protect. Policies that exist but cannot be seen are unlikely to produce the trust on which legitimate use depends.

The literature on human oversight raises a related problem. Jarrahi (2018) argues that AI is most effective in organisational decision-making as a complement to human judgement, supplying analytical breadth while humans handle uncertainty, equivocality, and contextual interpretation. Shneiderman (2020) formalises the point by separating level of automation from level of human control, rejecting the assumption that they vary inversely and arguing that systems combining high automation with high human control are more reliable and trustworthy. Davenport and Ronanki (2018) reach compatible conclusions from implementation experience, and Brynjolfsson and McAfee (2017) argue that automation transforms rather than eliminates professional roles. These are well-developed arguments, but their evidential base lies largely in corporate settings or in conceptual reasoning. Whether university managers actually position AI as advisory, how they verify its outputs, and where they locate accountability for AI-informed decisions remain open empirical questions. The augmentation model is often asserted as a design ideal; it is rarely observed as an institutional practice.

These strands point to four limitations that a further descriptive study would not resolve. The first concerns *stage*. Research has concentrated on intention and early adoption, leaving the routinised phase, where systems have become ordinary and questions of governance, readiness, and human judgement become empirically answerable, largely unexamined. The second concerns the *unit of analysis*. Treating the institution as a homogeneous adopter conceals the possibility that AI is embedded differently across organisational roles, which would make institution-level measures of adoption or capability misleading. The third concerns *evidence*. Claims about management AI rest disproportionately on capability analysis and self-report rather than on multi-source accounts of use. The fourth is conceptual, and arguably the most consequential for cumulative research. Studies in this area routinely invoke "adoption," "efficiency," "readiness," and "governance" without defining them, so that findings cannot be compared across studies whose central terms are operationalised differently or not at all. A field that cannot specify what it is measuring cannot accumulate what it finds. This study therefore specifies six constructs, each anchored in an identified theoretical tradition and operationalised for qualitative inquiry, before presenting evidence.

China offers a setting in which these questions can be addressed, though not one from which findings transfer unproblematically. Since the State Council's *New Generation Artificial Intelligence Development Plan* (2017), AI has been positioned as a strategic national priority with explicit implications for education, and Chinese universities have invested substantially in smart campus infrastructure, integrated data

platforms, and AI-supported administration. Crompton and Burke (2023) document a shift in the location of AI-in-higher-education research from the United States to China over their review period. Chinese institutions are therefore among those most likely to have moved beyond initial adoption into routine use. The same features that make the setting informative also call for caution. Adoption driven by national policy may follow coercive and mimetic logics rather than demonstrated local need (DiMaggio & Powell, 1983), and AI in Chinese education has been examined critically as a site where state strategy, commercial interests, and institutional practice intersect (Knox, 2020). A study in this setting cannot assume that adoption reflects functional value, and it must remain attentive to the governance and visibility questions that a policy-led trajectory makes more, not less, pressing.

This study examines AI in routinised management use at two public universities in Hubei Province, University A & B, which share a regional and national policy environment while differing in institutional profile. Drawing on interviews, focus group discussions, document analysis, and observation across four stakeholder groups, it addresses five research questions:

1. Which AI technologies are currently embedded in university management in Hubei Province??
2. How are these technologies applied within administrative processes?
3. What effects do management personnel perceive AI to have on operations and decision-making?

4. What challenges do the institutions encounter in integrating AI into management systems?

5. How do data generate by AI tools influence management decisions?

2. Theoretical Framework and Construct Specification

2.1 Theoretical foundations

Research on AI in higher education management has typically borrowed one adoption theory, most often TAM or UTAUT, and treated its constructs as sufficient. That strategy suits pre-adoption intention but not routinised institutional use. Explaining AI in routine use requires accounting for organisational coupling, institutional status, human capability, legitimacy, and the person–system relation at the same time, and no single theory was built for all five. This study therefore draws on five perspectives. They are selected not for coverage but because each answers a question the others cannot, and each is limited in a way the others partly repair.

2.1.1 Systems theory: where AI's value is located

General systems theory (von Bertalanffy, 1968) and its organisational application (Katz & Kahn, 1978) treat the organisation as an open system of interdependent subsystems whose performance depends on the information exchanged between them. Applied to the university, admissions, academic affairs, student services, finance, and planning become coupled subsystems rather than separate administrative domains. The analytical consequence is a shift in where AI's value should be sought. If AI is a set of task automations, its value is the sum of local efficiencies. If it is an integrative mechanism,

its value lies in changing what information moves between subsystems, how quickly, and with what fidelity. Systems theory is less helpful on two counts. It treats information flow as functionally neutral, and it has long been criticised for neglecting agency and conflict. It tells us to look for coordination effects but says nothing about who controls the coupling, whose activity becomes visible, or how actors resist. It is therefore used here to locate effects, not to explain how they are experienced.

2.1.2 Diffusion, TOE, and acceptance models: from adoption to routinisation Rogers's (2003) diffusion theory traces innovations from trial to routinisation, the stage at which an innovation loses its distinct identity and becomes ordinary organisational activity. Routinisation is the stage most relevant here and the least studied in higher education AI research. Diffusion theory, however, carries a pro-innovation bias that Rogers himself acknowledged, and its linear stage model fits poorly with institutional settings where adoption is mandated rather than chosen. The technology–organisation–environment framework (Tornatzky & Fleischer, 1990) moves the analysis to the organisational level by distinguishing technological, organisational, and environmental contexts. TOE is better described as a taxonomy than an explanatory theory, since it lists conditioning contexts without specifying mechanisms. Its value for this study is a single comparative prediction: two institutions sharing an environment, as WUT and CCNU do, may still diverge on organisational grounds. Acceptance models (Davis, 1989; Venkatesh et al., 2003) supply individual-level determinants of use. They predict intention, not institutional status, and so cannot distinguish a technology that is used from one that is taken for granted. They inform

the interview protocol here but are not tested.

2.1.3 Human capital and AI capability: the competence condition Human capital theory (Becker, 1964) locates productivity in members' competencies and predicts that returns to system investment depend on complementary investment in capability. Resource-based reasoning sharpens this: because technology is imitable, advantage derives from organisational resources that are not (Barney, 1991; Teece et al., 1997). Mikalef and Gupta (2021) operationalise the argument for AI across tangible resources, human skills, and intangible resources, showing that the latter two cannot be substituted by tangible investment. This finding is the basis for treating readiness as a construct rather than an implementation obstacle. The transfer to universities is not straightforward. Mikalef and Gupta's instrument was validated in firms, under a competitive logic that public universities share only partially. It also measures capability at firm level, assuming the internal homogeneity that the introduction questioned. Their "human skills" dimension, moreover, concerns competence in managing and deploying AI rather than in interpreting its outputs. This study retains the non-substitutability claim but disaggregates competence by role and by type.

2.1.4 Institutional theory: legitimacy and taken-for-grantedness Institutional theory holds that organisations adopt practices to secure legitimacy as well as functional advantage (Meyer & Rowan, 1977). Coercive, mimetic, and normative pressures explain why universities under one national policy regime adopt structurally similar systems (DiMaggio & Powell, 1983). Scott's (2014) cultural-cognitive pillar supplies what diffusion theory lacks: an observable criterion for institutionalisation. A

practice is institutionalised when it is no longer justified but simply assumed, which can be detected in how participants talk about a technology rather than in deployment statistics. Meyer and Rowan's concept of decoupling, where formal structure is adopted for legitimacy while practice diverges, frames the analysis of governance. The theory's familiar weakness is its emphasis on convergence at the expense of internal variation and agency. It predicts isomorphism between institutions but is largely silent on difference within them. The present study turns this weakness into a question. It asks whether legitimacy depends on visibility to internal stakeholders, not only on conformity to external regulators.

2.1.5 Socio-materiality and human-centred AI: the mediation condition

The preceding perspectives say little about the relation between the system and its user. Orlikowski (2000) argues that technologies have no fixed effects but are enacted in practice. Leonardi (2011) specifies this through imbrication: users who experience a technology as constraining change the technology, while those who experience it as affording change their routines. This predicts that systems and administrative routines will co-evolve. Socio-material accounts are analytically rich but often hard to falsify, so they are used here to interpret integration processes rather than to generate predictions. Shneiderman's (2020) human-centred AI framework supplies the normative complement. By separating level of automation from level of human control, it makes intelligible an arrangement that substitution models cannot: high automation under high human control. It is a design framework rather than an empirical theory of organisational use, and whether institutions actually realise this

configuration is precisely what the study examines.

1.6 Integration: a four-condition framework. Read together, the five perspectives specify four conditions for AI to contribute to university management:

- Integration:** AI must couple subsystems, not merely automate tasks within them (systems theory).
- Normalisation:** AI must pass from trial to taken-for-granted routine (diffusion theory; the cultural-cognitive pillar).
- Interpretive capability:** users must be able to read and critically evaluate outputs (human capital and AI capability theory).
- Governance legitimacy:** oversight must be visible to those subject to the systems (institutional theory).

Sociometrical and human-centred perspectives specify the relation across which these conditions operate: AI mediates between institutional data and human decision-makers rather than substituting for either. We advance the conditions as jointly necessary, but a two-site qualitative design cannot establish necessity. The claim is therefore stated as a framework to be tested through the propositions in Section 2.3, not as a conclusion.

2.2 Construct specification

Six constructs are derived from the framework. In a qualitative design they function as sensitising concepts (Blumer, 1954), directing attention without predetermining findings. Each is nonetheless specified with the precision expected of a measured construct, which makes the analysis auditable and prepares the constructs for later scale development. Operational indicators and data sources are summarised in Table 1.

C1. AI infrastructural embeddedness is the degree to which AI systems are constituted as ordinary elements of institutional infrastructure rather than innovations under evaluation. Rogers (2003) defines routinisation as the stage at which an innovation loses its distinct identity. Cooper and Zmud (1990) establish that acceptance, routinisation, and infusion are distinct states, not points on one continuum. Scott (2014) supplies the observable criterion of taken-for-grantedness. Three sub-dimensions follow: breadth (domains in which AI is present), depth (reliance rather than mere availability), and taken-for-grantedness (whether systems are described in the vocabulary of ordinary work or of innovation). The third is the discriminating dimension, because breadth and depth can be high while a technology is still framed as novel. C1 differs from adoption intention, which concerns a pre-use state, and from usage frequency, which ignores institutional status. It is closest to organisational assimilation but adds an interpretive criterion that assimilation measures omit.

C2. Administrative process integration is the extent to which AI systems are coupled to administrative workflows and to one another, altering information flow between subsystems. Coordination theory (Malone & Crowston, 1994) specifies the mechanism: technologies change performance by changing how dependencies between activities are managed. Task–technology fit (Goodhue & Thompson, 1995) adds that effects depend on the match between capability and task. Imbrication (Leonardi, 2011) frames integration as mutual adjustment rather than a state reached at implementation. Following Zuboff (1988), two modes are distinguished: process substitution

(automating) and information consolidation (informating). A third sub-dimension, inter-unit coupling, captures whether integration changes flow between subsystems and not only within them.

C3. Perceived administrative efficiency and responsiveness refers to stakeholders' assessment of change in time, effort, error, and latency attributable to AI. Melville et al. (2004) argue that IT value is realised at the process level before it appears organisationally. DeLone and McLean (2003) establish perceived net benefit as a legitimate construct. Three sub-dimensions correspond to distinct mechanisms: processing efficiency, data reliability, and institutional responsiveness (compression of the interval between an event and its visibility to management). Responsiveness derives from informing rather than automating, and it is the dimension that links C2 to C6. Perceived efficiency is not measured efficiency. The construct is perceptual because perception conditions subsequent managerial behaviour, and the absence of objective process metrics is recorded as a limitation in Section 6.

C4. Human readiness is the capability of institutional actors to operate AI systems and, critically, to interpret and evaluate their outputs. Human capital and resource-based reasoning establish that capability complements technology (Becker, 1964; Mikalef & Gupta, 2021). Absorptive capacity (Cohen & Levinthal, 1990) adds that capability is path-dependent and cannot be acquired through isolated training events. Three sub-dimensions are distinguished: operational competence, interpretive competence (understanding what an output measures, what it omits, and what action it warrants), and self-

efficacy (Bandura, 1997). The operational–interpretive distinction is central to the argument. C4 is narrower than general AI literacy (Long & Magerko, 2020) or educator data literacy (Mandinach & Gummer, 2016), being restricted to managerial and academic use of institutional outputs, but it shares their emphasis on critical evaluation over operation. Lebovitz et al. (2022) provide the closest empirical precedent: professionals incorporated AI outputs only where they interrogated them against their own knowledge, and this practice was unevenly distributed across departments of one organisation.

C5. AI governance and privacy assurance is the extent to which stakeholders perceive mechanisms governing data access, protection, transparency, and accountability to be present and visible. Institutional theory supplies the function, legitimacy, and the risk of decoupling (Meyer & Rowan, 1977). IT and data governance research supply the structure: decision rights and accountability (Weill & Ross, 2004) across data principles, quality, metadata, access, and lifecycle (Khatri & Brown, 2010). Ethics frameworks supply the content (Floridi et al., 2018; Jobin et al., 2019; Nguyen et al., 2023). Three sub-dimensions are distinguished: formal provision, enacted practice, and perceived visibility. The gap

between the first two is decoupling. The third conditions trust, which is treated as an outcome rather than a component, following Mayer et al.'s (1995) separation of trustworthiness antecedents from trust itself.

C6. Decision augmentation is the extent to which AI-generated information informs managerial decisions while judgement and accountability remain with humans. Bounded rationality (Simon, 1955) and the distinction between programmed and non-programmed decisions (Gorry & Scott Morton, 1971) separate the scheduling functions AI substitutes for from the strategic judgements it informs. Jarrahi (2018) specifies the division of labour, and Shneiderman (2020) and Parasuraman et al. (2000) locate the arrangement at the analysis stage of automation rather than at decision selection. Three sub-dimensions are distinguished: informational reliance, verification practice, and decision authority. C6 is not a preference measure of algorithm aversion (Dietvorst et al., 2015) or appreciation (Logg et al., 2019). It characterises an institutional arrangement in which verification and authority are specified independently of how favourably the system is regarded. Lebovitz et al.'s (2022) contrast between engaged and unengaged augmentation implies that C4 and C5 jointly condition C6.

Table 1. Construct specification summary

Construct	Sub-dimensions	Principal theoretical anchors	Operational indicators	Sources
C1. AI infrastructural embeddedness	Breadth; depth; taken-for-grantedness	Rogers (2003); Cooper & Zmud (1990); Scott (2014)	Operational vs. aspirational vocabulary; unprompted range of systems named; framing as ordinary vs. exceptional; presence in institutional strategy	All four
C2. Administrative process integration	Process substitution; information consolidation; inter-unit coupling	von Bertalanffy (1968); Malone & Crowston (1994); Goodhue & Thompson (1995); Zuboff (1988); Leonardi (2011)	Functions supported; integration mode; cross-unit information flow; routine–system co-evolution	All four
C3. Perceived efficiency and responsiveness	Processing efficiency; data reliability; institutional responsiveness	Melville et al. (2004); DeLone & McLean (2003)	Reported reduction in manual processing and error; event-to-visibility latency; observed workflow	Interviews; FGD; observation
C4. Human readiness	Operational competence; interpretive competence; self-efficacy	Becker (1964); Cohen & Levinthal (1990); Mikalef & Gupta (2021); Lebovitz et al. (2022)	Confidence by role; operational vs. interpretive difficulty; training vs. peer learning; help-seeking	Interviews; FGD; observation
C5. Governance and privacy assurance	Formal provision; enacted practice; perceived visibility	Meyer & Rowan (1977); Weill & Ross (2004); Khatri & Brown (2010); Nguyen et al. (2023)	Expressed data concerns; policy reference; observed access control; documentary provisions	Interviews; FGD; documents; observation
C6. Decision augmentation	Informational reliance; verification practice; decision authority	Simon (1955); Jarrahi (2018); Shneiderman (2020); Lebovitz et al. (2022)	Use of outputs in planning; pre-decision verification; stated locus of authority; observed meeting use	All four

2.3 Propositions

The constructs form a nomological network through which the four conditions operate. Five propositions are stated so that the findings can be read against them; they are restated in Section 5.6 as hypotheses for quantitative testing. P1. Embeddedness (C1) and process integration (C2) are positively associated with perceived efficiency and responsiveness (C3), because value is realised first at the process level (Melville et al., 2004) and coordination gains derive from inter-unit coupling (Malone & Crowston, 1994). P2. Human readiness (C4), particularly interpretive competence, strengthens the association in P1, because returns to technology depend on complementary, path-dependent capability (Cohen & Levinthal, 1990; Mikalef & Gupta, 2021). P3. C3 is positively associated with decision augmentation (C6) through informing rather than automating, since decision effects follow from new information rather than substituted effort (Zuboff, 1988). P4. Governance and privacy assurance (C5) strengthens the association in P3, because legitimacy conditions acceptance (Meyer & Rowan, 1977) and opacity without interrogation produces unengaged augmentation (Lebovitz et al., 2022). P5. C1 and C4 vary systematically by organisational role, so institution-level aggregation obscures meaningful variance. This proposition was generated abductively during analysis (Section 3.5) and bears on the construct validity of existing institution-level adoption and capability measures.

3. Methods

3.1 Design

The study employed a qualitative phenomenological design (Moustakas, 1994), appropriate because the research questions concern how AI in university management is experienced and interpreted by those who work with it, rather than the magnitude of its effects. Phenomenological inquiry seeks the essence of a phenomenon as it presents itself in lived experience, moving through textural description (what was experienced), structural description (how it was experienced, under what conditions), and composite essence. Interpretative phenomenological analysis (Smith et al., 2009) was applied alongside thematic analysis (Braun & Clarke, 2006) to preserve attention to how meaning varied across institutional positions.

3.2 Setting

The study was conducted at two public universities in Hubei Province. University A is a comprehensive research university whose digital strategy is oriented toward smart campus infrastructure, automated scheduling, and student service platforms. University B is a leading normal university whose strategy emphasizes predictive analytics, AI cloud services, and intelligent campus governance frameworks. Both had moved beyond pilot deployment, making them suitable sites for examining routine institutional use. Their differing strategic emphases, within a shared national and regulatory environment, permit examination of the TOE prediction that organizational context conditions adoption profile independently of environmental context.

3.3 Participants and sampling

Purposive sampling was used, combining maximum-variation, snowball, and typical-case strategies (Patton, 2015). Inclusion required direct working experience with AI-supported management systems in an institutional role. Fifteen participants took part in semi-structured interviews: five administrators, four IT staff, three faculty members, and three

students, drawn from both institutions (Table 2). A further ten participants took part in two focus group discussions, one at each site, each comprising an administrator, an IT staff member, a faculty member, an administrative officer, and a student. Recruitment continued to the point of data saturation, at which further interviews produced no new themes (Guest et al., 2006).

Table 2. Interview participant profile

Code	Role	University	Gender	Age group	AI experience	Service/study
A1	Administrator	UNIVERSITY A	M	45–54	Advanced	10 years
A2	Administrator	UNIVERSITY A	F	35–44	Moderate	6 years
A3	Administrator	UNIVERSITY A	M	35–44	Moderate	7 years
A4	Administrator	UNIVERSITY B	F	45–54	Advanced	10 years
A5	Administrator	UNIVERSITY B	M	35–44	Moderate	8 years
IT1	IT staff	UNIVERSITY A	M	25–34	Advanced	4 years
IT2	IT staff	UNIVERSITY A	F	25–34	Advanced	4 years
IT3	IT staff	UNIVERSITY B	M	35–44	Advanced	8 years
IT4	IT staff	UNIVERSITY B	F	25–34	Advanced	3 years
F1	Faculty	UNIVERSITY A	F	35–44	Moderate	8 years
F2	Faculty	UNIVERSITY A	M	25–34	Basic–moderate	4 years
F3	Faculty	UNIVERSITY B	F	35–44	Moderate	8 years
S1	Student	UNIVERSITY A	M	18–24	Moderate	Year 4
S2	Student	UNIVERSITY B	F	18–24	Moderate	Year 3
S3	Student	UNIVERSITY B	M	18–24	Basic–moderate	Recent graduate

3.4 Data collection

Four instruments were used to permit methodological triangulation (Patton, 2015), with each instrument mapped to the constructs it was best positioned to evidence (Table 1, final column). *Semi-structured interviews* lasting 45–60 minutes addressed four domains aligned to the research questions and constructs: the AI tools in use and their administrative

functions (C1, C2); perceived effects on workflow, efficiency, and decision-making (C3, C6); obstacles encountered during integration (C4); and the influence of AI-generated data on managerial choices, including data governance concerns (C5, C6).

Focus group discussions elicited collective interpretation, allowing participants from different institutional positions to compare

experiences and surface shared organisational norms, particularly relevant to C1, where taken-for-grantedness is a group-level rather than individual property. *Document analysis* (Bowen, 2009) covered eight institutional texts (Table 3) selected for direct relevance to AI deployment in administrative and academic management: policy frameworks, transformation reports, system manuals, implementation notices, and performance evaluations. *Non-participant observation*

comprised six sessions of 45–60 minutes in academic affairs offices, campus administration centres, faculty offices, student service centres, IT management offices, and administrative planning units, focused on interaction between users and AI-supported systems in routine work (Creswell & Poth, 2018). Observation was the primary means of evidencing enacted rather than stated practice, particularly for C4 and C5.

Table 3. Institutional documents analysed

Code	Institution	Document type	Year	Relevance
D1	University A	Smart Campus Development Policy	2022	Digital campus infrastructure framework
D2	University A	Digital Transformation Annual Report	2023	AI dashboards; administrative automation
D3	University A	Automated Scheduling System Manual	2023	Scheduling algorithm; room allocation
D4	University A	Student Service Chatbot Implementation Notice	2022	Chatbot deployment for student enquiries
D5	University B	Intelligent Campus Governance Policy	2023	AI governance; ethical data practice
D6	University B	AI Systems Performance Evaluation Report	2024	Predictive analytics; administrative AI
D7	University B	Predictive Analytics Dashboard Guide	2023	Monitoring of academic trends
D8	University B	AI-Based Student Support System Update	2024	Student service automation

3.5 Analysis

Analysis proceeded in five stages. Interview and focus group recordings were transcribed verbatim; observational notes and document extracts were organized into a single analytical corpus and read repeatedly to achieve immersion. Open coding generated descriptive codes for meaningful units (Strauss & Corbin,

1998). Codes were grouped into conceptual categories separately for each instrument, preserving the contextual meaning of each source. Categories were synthesized into overarching themes through iterative comparison across instruments. Interpretative phenomenological analysis was then applied to examine how participants in different

institutional roles made sense of the same technologies. Finally, textural and structural descriptions were integrated into a composite essence. Coding was abductive rather than purely inductive: the six constructs functioned as sensitizing concepts orienting attention, while codes not accommodated by them were retained and permitted to generate new categories. Role-differentiated embedding, reported in Section 4.1, emerged in this way and was not anticipated by the framework. Thematic prevalence was recorded qualitatively as strongly, moderately, or weakly present, according to whether a theme appeared across multiple participant groups and multiple instruments, in several instances but unevenly, or only occasionally and in a single source. These are indicators of analytical prominence, not statistical frequencies.

3.6 Trustworthiness

Trustworthiness was addressed against the four criteria specified by Lincoln and Guba (1985).

Credibility: triangulation across four instruments, with each theme assessed against all four data sources (Table 4); member checking, allowing participants to review and confirm interpretations; peer debriefing with qualitative researchers to test the coding structure. *Transferability*: thick description of setting, participants, and institutional context. *Dependability*: documentation of an analytical audit trail recording coding decisions and category revisions. *Confirmability*: bracketing practiced during transcription and coding to hold the researcher's prior assumptions about AI in abeyance, with reflexive memos recording points at which prior assumptions were challenged by the data.

4. Findings

Six themes were identified, corresponding to the six constructs. Table 4 summarizes their support across the four instruments.

Table 4. Triangulation matrix

Construct / theme	Interviews	Focus groups	Documents	Observation
C1. AI embedded as institutional infrastructure	√	√	√	√
C2. Integration into administrative processes	√	√	√	√
C3. Efficiency and institutional responsiveness	√	√	—	√
C4. Uneven human readiness	√	√	—	√
C5. Governance and privacy assurance	√	√	√	—
C6. AI as advisory, not autonomous	√	√	√	√

4.1 C1: From innovation to infrastructure

The most consistent finding across all four instruments is that participants do not describe AI as an innovation under evaluation. They describe it as part of the ordinary structure

through which university work is conducted. The vocabulary is operational rather than aspirational: what the systems do now, where they are used, and how they shape daily tasks. Applying Scott's (2014) cultural-cognitive

criterion, this constitutes institutionalization rather than adoption.

Six technology categories recurred: smart campus platforms, AI reporting and analytics dashboards, predictive analytics systems, automated scheduling engines, chatbot-based service systems (predominantly WeChat-integrated), and AI cloud services supporting administrative processing. An administrator at University A described the composite as unremarkable: “The smart campus platform, reporting dashboard, and chatbot system have become an integral part of our daily operations. We use them regularly for attendance monitoring, student questions, and administrative reporting” (A1).

Crucially, this normalization was not evenly distributed across roles. Administrators encountered AI principally through reporting, monitoring, and planning interfaces. IT staff encountered it as technical architecture requiring maintenance, integration, and security management: “Most departments now rely on analytics dashboards and cloud-based services to provide institutional information in a timely manner” (IT2). Faculty encountered it through learning analytics and attendance systems: “Learning analytics dashboards are making it easier for us to monitor student participation and engagement than ever before” (F1). Students encountered it almost exclusively at the service interface: “The chatbot and online service systems are typically the quickest way to find out about university procedures and campus services” (S2).

Institutional documents corroborated this embedding at the level of formal strategy. Smart campus systems were tied in policy to attendance, campus monitoring, and resource management; dashboards to institutional

performance tracking; scheduling systems to classroom allocation; chatbots to student communication. Observation confirmed material presence: across all six sites, the systems described in interviews and documents were in active use rather than in planned deployment. The analytical significance is that C1 is not a single institution-level value. Embeddedness is stratified by role, an outcome the framework did not anticipate.

4.2 C2: Integration into administrative processes

The second theme concerns how these technologies enter specific administrative work. Participants located AI within admissions administration, timetable generation, classroom allocation, institutional reporting, student communication, resource coordination, and performance monitoring.

Two integration patterns emerged, corresponding to Zuboff's (1988) distinction. The first is *process substitution*, automating: tasks previously executed manually are now executed algorithmically with human verification. Automated scheduling is the clearest instance. “The automated scheduling system decreases timetable conflicts because it takes into account classroom availability, teacher schedules and course needs simultaneously” (A3). Observation in the academic affairs office confirmed the pattern, including its human residue: staff generated timetables through the system, then verified outputs manually before confirmation.

The second is *information consolidation*, informing: systems that do not replace a task but change what information is available while performing it. Dashboards aggregate data

previously distributed across departmental records into a single interface. “The platform can summarise from existing databases, which eliminates repetitive manual tasks in the process of AI reporting” (IT1). This pattern matters because it alters the informational basis of administrative work without altering the work’s formal structure, and, as Section 4.3 shows, it accounts for the more consequential of the reported effects.

Focus group participants emphasised a systems-level consequence neither pattern predicts individually: integration reduces inter-departmental communication delay. When a scheduling system produces a timetable, the output is immediately visible to academic departments, room management, and faculty simultaneously, removing a sequence of notification steps and eliminating duplicate data entry. This is the coordination effect systems theory predicts, and it was described as more valuable than the task-level automation that produced it.

The co-evolution Leonardi (2011) describes was also visible. Participants reported adjusting administrative routines around system capabilities, scheduling planning cycles to system output rhythms, restructuring report formats around dashboard categories, rather than only fitting systems to existing routines.

4.3 C3: Efficiency and institutional responsiveness

Efficiency was the most frequently reported benefit, supported strongly by interviews, focus groups, and observation, and implied by the systems described in institutional documents.

Participants described three mechanisms. First, reduction of manual processing: reports previously requiring collation across offices are generated from consolidated data. “With the digital dashboards we can access institutional information in real time; before, we had to go back to different offices to gather information for preparing a report” (A1). Second, reduction of error: automated processing removes transcription and aggregation errors characteristic of spreadsheet-based reporting. Third, and most consequential managerially, compression of the interval between an institutional event and its visibility to management. “Real-time data allows us to react to administrative issues faster than if it had to be prepared manually” (A5).

The third mechanism supports a change in managerial posture rather than merely in speed. Where reporting cycles previously determined when administrators learned of a developing problem, continuous monitoring allows detection within the cycle. Administrators described identifying under-enrolled courses early in a semester and reallocating provision accordingly, an intervention the previous reporting rhythm did not permit. This is the informing effect rather than the automating one, and it is the mechanism through which C2 translates into C6.

Students located efficiency at a different point in the system: “The chatbot reduces time, since students can receive simple information without having to wait in the office” (S1). From the administrative side, the same system removes a class of repetitive enquiry from staff workload, redirecting attention to cases requiring judgement, consistent with Brynjolfsson and McAfee’s (2017) account of role transformation.

4.4 C4: Uneven human readiness

Efficiency claims were consistently qualified. Participants across roles identified staff capability, not system capability, as the binding constraint, supporting the proposition that C4 moderates the relationship between C1/C2 and C3.

The constraint has two components. The first is operational: navigating complex interfaces and system functions. The second, more significant, is interpretive: reading analytics outputs correctly. “While all the information the dashboard gives is important, some staff need further training to ensure they are able to interpret the indicators correctly” (A2). A University B administrator stated the point directly: “It’s not the technology itself that’s the big hurdle, it’s the fact that employees need to feel confident enough to make the most of the system” (A4).

Faculty articulated the interpretive requirement in specifically professional terms: “Learning analytics tools are helpful, but they should be interpreted in the proper light and context before making judgements based on the data” (F1). The competence at issue is not operating a dashboard but knowing what an engagement indicator does and does not warrant, a distinction that existing AI capability instruments, which measure human skills at the level of technical and managerial competence (Mikalef & Gupta, 2021), do not currently capture.

Readiness was distributed unevenly and was addressed differently at the two sites. At University A, adaptation was supported substantially through informal peer learning, with more experienced colleagues assisting

others. At University B, participants described formal training sessions accompanying system introduction, while noting that discrete training events are insufficient for continuously evolving systems: “When new digital systems are introduced, training sessions become necessary as users must get to know the reporting and functions of the system” (IT3).

Observation corroborated the pattern in a form participants did not report: staff consulting colleagues or IT personnel when navigating dashboards, and administrators seeking verification of data interpretations. Notably, this did not present as resistance. Participants were broadly positive about the systems; the difficulty was capability, not willingness, a distinction that acceptance-model framings, which treat effort expectancy as a determinant of intention, do not readily accommodate at the post-adoption stage.

4.5 C5: Governance and privacy as conditions of legitimacy

Governance emerged not as a compliance overlay but as a condition under which participants regarded AI systems as acceptable. Administrators framed governance as boundary-setting around institutional data. “While AI dashboards offer useful information for planning and monitoring, it is crucial to set boundaries around access to the data and the use of the information” (A4). IT staff framed it operationally, as continuous technical practice: “Data security is an ongoing process; we need to regularly review system access, security protocols, and ensure that institutional databases continue to be secure” (IT1). The distinction matters analytically: governance is enacted in routine technical work, not only declared in policy, Scott’s (2014) regulative pillar realised through practice rather than rule.

Students introduced a dimension the staff accounts did not contain. While valuing service convenience, several expressed discomfort about data collection through smart campus systems and facial-recognition access: “Some students may worry about the collection and storage of their personal information in digital systems, while smart campus services are convenient” (S2). The student experience of AI thus contains both convenience and surveillance sensitivity, engaging directly the privacy and human-centred principles that Nguyen et al. (2023) identify.

Document analysis provided the strongest formal evidence. University B’s *Intelligent Campus Governance Policy* and data security framework explicitly link AI deployment to transparency, data protection, and ethical practice, indicating that governance is part of the institutional logic through which these systems are justified, not a subsequent correction.

Focus group discussion established the connective claim, supporting the second proposed relationship: trust in AI systems tracked the visibility of safeguards. Participants valued analytics tools more highly where oversight mechanisms appeared to be in place. Governance, on this evidence, is not a constraint on the value of AI systems but a precondition of it.

Observation, however, showed governance to be unevenly enacted. Protective practice was visible in some settings, restricted dashboard access, verification of sensitive outputs, reliance on technical support for interpretation, and less visible in others. The gap between policy-level formalisation and everyday enactment is itself a finding and corresponds to the decoupling of formal

structure from operational practice that Meyer and Rowan (1977) identify as a characteristic institutional response to legitimacy pressure.

4.6 C6: AI as advisory, not autonomous

Across every participant group, instrument, and institution, AI was positioned as informing decisions rather than making them. Administrators described analytics as expanding what could be seen, while locating judgement firmly with humans. “While predictive analytics can identify patterns and potential threats, an administrator must still analyse the findings and decide on the best action to take” (A5). Another framed the contribution as timeliness rather than authority: “AI systems deliver information to help plan discussions, and decisions are made based on information that is up to date, not prepared weeks ago” (A3).

Focus groups extended this from individual to collective decision-making. Analytics outputs function as a shared starting point for deliberation: management teams review dashboards together during planning meetings and use the data to structure discussion of priorities and allocation. AI thus enters the decision process as a common informational reference, not as a recommendation engine, a role consistent with Jarrahi’s (2018) account of AI handling analytical breadth while humans handle equivocality.

Observation confirmed the pattern behaviourally. Administrators referenced AI-generated reports during planning discussions and, where predictive outputs indicated enrolment change, consulted additional sources or colleagues before acting. Verification preceded action consistently.

In Shneiderman's (2020) terms, participants describe and endorse a high-automation, high-human-control configuration rather than a trade-off between the two. The uniformity of this positioning, across all four instruments, both institutions, and roles with very different relationships to the technology, is unusual in

the dataset and suggests a settled institutional norm rather than a stated aspiration.

4.7 Cross-case comparison

The two institutions differ consistently in implementation orientation while converging on outcome (Table 5).

Table 5. Comparative implementation orientation by construct

Construct	University A	University B
C1. Most visible technologies	Smart campus, WeChat chatbot, automated scheduling, reporting dashboards	Smart campus, predictive analytics dashboards, AI cloud services, student service platforms
C2. Primary integration focus	Service delivery, scheduling, administrative coordination	Institutional monitoring, analytics, strategic review
C3. Locus of efficiency gain	Workflow automation and service responsiveness	Information accessibility and performance oversight
C4. Readiness support mechanism	Informal peer learning	Formal institutional training
C5. Governance emphasis	Operational system administration	Policy frameworks and institutional accountability
C6. Decision orientation	Operational, short horizon	Strategic, longer-horizon
Overall pattern	Operational and service-oriented integration	Analytics and governance-oriented integration

The divergence is one of orientation, not maturity. Both institutions have moved AI from optional innovation to management infrastructure; they have done so along different axes consistent with their institutional missions. This supports the TOE prediction (Tornatzky & Fleischer, 1990) that organizational context conditions adoption profile independently of a shared environmental context and qualifies models treating AI implementation as a single developmental sequence.

4.8 Composite essence

Integrating the textural and structural dimensions yields the following essence. AI in university management is experienced as an expansion of the informational and analytical reach of institutional actors that leaves the locus of managerial judgement unchanged. Participants encounter AI as an infrastructure that alters how institutional information circulates, what is visible, how quickly, and to whom, without altering who is accountable for acting on it. The phenomenon is therefore best characterized not as automation of

management but as *mediation* of management. Three conditions structure this experience, corresponding to constructs C2, C4, and C5: technological integration across administrative subsystems, human capability to interpret system outputs, and governance frameworks that render the systems legitimate to those subject to them. Where any is absent, participants' accounts suggest the informational expansion does not translate into managerial value.

5. Discussion

The clearest divergence between these findings and much of the existing literature concerns adoption stage. A substantial body of work asks whether universities are adopting AI, or projects the value of future adoption; acceptance-model studies measure intention to adopt (Chatterjee & Bhattacharjee, 2020; Wang et al., 2021). Participants in this study did not describe adoption. They described systems that had already become unremarkable, Rogers's (2003) routinization stage, and Scott's (2014) cultural-cognitive pillar in operation. This supports Williamson and Eynon's (2020) infrastructural reading and extends it phenomenologically. Their argument concerns a hidden architecture of data systems reorganizing institutional practice; the present findings indicate that this architecture is also embedded in the lived routines of administrators, staff, faculty, and students, to the point that it is described in the vocabulary of ordinary work. Cultural normalization is the marker distinguishing institutionalization from adoption, observable in how participants speak about systems rather than in deployment statistics. This has a methodological implication: research designs measuring adoption intention are mis-specified for

institutions at this stage, and post-adoption constructs of the kind proposed here are required.

The finding that embeddedness (C1) is stratified by institutional role complicates a common analytical move. Reviews frequently characterize AI integration as an institution-level property. The present data indicate that a single institution can be simultaneously at different depths of integration depending on where one stands within it. This has methodological implications. Studies sampling only administrators will describe a management-analytics phenomenon; studies sampling only students will describe a service-automation phenomenon; both will be accurate and incomplete. It also refines Mikalef and Gupta's (2021) AI capability construct: if capability dimensions are distributed unevenly across organizational roles, firm-level or institution-level measures aggregate over meaningful internal variance. And it has practical implications: institutional AI strategies assuming uniform experience will misallocate training, governance attention, and communication effort.

The efficiency findings align with Brynjolfsson and McAfee's (2017) account of AI-enabled productivity gains and Davenport and Ronanki's (2018) implementation evidence. The more consequential finding is the qualification participants attached to them, which supports the proposed moderating role of C4. The constraint identified is not operational competence but interpretive competence, the capacity to read analytics output critically, understand what it measures, and judge what action it warrants. This is a higher-order capability than system training typically addresses, and it is the capability on

which the decision-support value of these systems depends. Human capital theory (Becker, 1964) anticipates that returns to technology investment are conditional on member competence; the present findings specify the competence at issue and locate it in interpretation rather than operation. This suggests a refinement to the human-skills dimension of AI capability measurement (Mikalef & Gupta, 2021), which addresses technical and managerial competence without distinguishing interpretive competence as a separate component.

Lebovitz et al. (2022) provide the closest precedent and the most useful interpretive frame. Studying radiologists working with diagnostic AI, they found that professionals incorporated system outputs into their judgements only where they enacted what the authors term AI interrogation practices, deliberate work relating their own knowledge claims to the system's, and that departments lacking such practices exhibited *unengaged augmentation*, in which outputs were available but disregarded. The present findings reproduce this pattern in an administrative rather than clinical setting: participants who described confident use of analytics invariably also described interrogating outputs, while those reporting difficulty described the outputs as information they could not act on. The theoretical implication is that interpretive competence is not a threshold condition for use but a condition for *consequential* use, which is why it constrains C6 as well as C3.

Cohen and Levinthal's (1990) absorptive capacity concept explain why this constraint is not readily relieved by training events. If the capacity to recognize, assimilate, and apply new information depends on prior related

knowledge, then interpretive competence is path-dependent and accumulates through exposure rather than instruction. This is consistent with participants' description of readiness as developing gradually, and with the observation that discrete training sessions accompanying system introduction were reported as necessary but insufficient. The peer-learning pattern at University A is worth noting for practice. Informal knowledge transfer was doing substantial adaptive work that formal training did not cover, consistent with accounts of collaborative problem-solving in technology adoption (Selwyn, 2021) and with Tsai et al.'s (2019) finding that distributed capability shapes institution-wide analytics adoption. Institutions relying implicitly on this mechanism are relying on an unmanaged resource.

The governance findings depart from framings that treat ethics and privacy as constraints traded off against capability. Participants' accounts indicate the opposite relation, supporting the second proposed relationship: perceived governance quality was a condition of the systems' perceived value, with trust tracking the visibility of safeguards. This is consistent with institutional theory's account of legitimacy (Meyer & Rowan, 1977; Scott, 2014) and refines it. Legitimacy here is secured not primarily through external regulatory conformity but through internal visibility, stakeholders' ability to see that oversight exists. It also engages the algorithmic opacity problem (Pasquale, 2015): administrators reported acting on outputs whose derivation they could not fully inspect, which is the condition under which explainability requirements (Jobin et al., 2019; Nguyen et al., 2023) become operationally rather than philosophically urgent. The observed gap between policy-level

formalization and uneven everyday enactment is the practical form this problem takes and corresponds closely to the decoupling Meyer and Rowan (1977) describe. Governance existing in documents but not in routine practice satisfies neither the legitimacy function nor the protective one. Read against Khatri and Brown's (2010) five decision domains, the pattern is more specific than a general formalization gap. Institutional documents at both sites addressed data principles and, at University B, data access; the domains least visible in either documents or practice were metadata and data lifecycle, precisely the domains bearing on whether users can establish what an indicator measures and how current it is. This is the same deficiency that appears in C4 as interpretive difficulty, which suggests that what is experienced by staff as a training problem is partly a governance problem in a different guise. Institutions treating the two as separate agendas may be resourcing training to compensate for absent metadata governance.

The uniformity of the advisory positioning (C6) across roles, instruments, and institutions is striking, and consistent with both Jarrahi's (2018) human-AI symbiosis model and Shneiderman's (2020) framework. Two readings are possible. The first is normative: participants have arrived at a considered view that contextual, ethical, and political dimensions of institutional decisions are not tractable to current systems, an application of bounded rationality (Simon, 1955) in which the system extends the analytical bound without addressing the value-laden component of the decision. The second is developmental: the settlement reflects present system capability and may shift as capability grows. The data support the first reading more strongly,

participants grounded the position in what AI cannot know about institutional context rather than in what it cannot yet compute, but the second cannot be excluded from a single-timepoint study. This is a question for longitudinal research, and a consequential one: an advisory settlement maintained by norm is more durable than one maintained by capability limits.

The behavioral literature on algorithmic reliance suggests a third reading that the present data cannot adjudicate. Dietvorst et al. (2015) show that reliance falls sharply after users observe a system err, while Logg et al. (2019) find that people often prefer algorithmic to human judgement absent such evidence. The advisory settlement observed here is compatible with either an aversion pattern maintained by past error or an appreciation pattern moderated by institutional accountability norms; participants were not asked about system failures, and no observed episode involved one. Framing the arrangement in Parasuraman et al.'s (2000) terms is more defensible on the available evidence: automation is high at the information acquisition and analysis stages and near absent at decision selection and action implementation. Whether that allocation reflects considered judgement, accumulated experience of error, or institutional accountability structures is a question a design distinguishing the three would need to address.

The study's principal theoretical claim is that the five frameworks are jointly necessary. Systems theory explains the integrative function distinguishing AI infrastructure from discrete task automation but cannot explain why integration proceeded differently at two structurally comparable institutions. Diffusion

theory explains the movement from trial to routine but treats the adopting unit as more homogeneous than the role-differentiated evidence supports; TOE accommodates the institutional divergence that diffusion theory alone does not. Human capital and AI capability theory identify the competence constraint but do not explain why governance conditions perceived value. Institutional theory explains the legitimacy function of governance but not the operational mechanics of integration. Sociometrical and human-centered perspectives specify the mediating relation across which all four conditions operate.

The integrated account specifies four non-substitutable conditions: subsystem integration, normalization into routine practice, interpretive capability among users, and visible governance. The comparative evidence indicates these can be satisfied through different institutional configurations, UNIVERSITY A's operational–peer-learning configuration and UNIVERSITY B's analytical–formal-governance configuration, which suggests they are functional requirements rather than a prescribed implementation path.

The six constructs specified can be restated as a measurement agenda. The propositions advanced in Section 2.6 were supported in the qualitative evidence as follows: P1 and P3 were supported across all contributing instruments; P2 was supported through participants' consistent attribution of variance in realized benefit to capability rather than provision; P4 was supported through the association between perceived governance visibility and willingness to act on AI-generated information; and P5 emerged abductively and was subsequently supported across all four

instruments. Qualitative support is not statistical confirmation, and the propositions remain hypotheses.

Three measurement priorities follow. First, existing AI capability instruments (Mikalef & Gupta, 2021) treat human skills as a single dimension; the present findings indicate that operational and interpretive competence behave differently and should be measured separately, with interpretive competence operationalized along the lines of the interrogation practices Lebovitz et al. (2022) identify rather than as self-reported proficiency. Second, governance measurement should distinguish formal provision from perceived visibility, since the decoupling observed here means the two can diverge and only the latter appears to condition trust; Khatri and Brown's (2010) decision domains provide a structure for the former, but no established instrument captures the latter in an educational setting. Third, and most consequentially for cumulative research, P5 implies that institution-level measures of AI adoption and capability aggregate over role-level variance that is theoretically meaningful. Multilevel designs treating role as a grouping variable would establish whether the variance components warrant this, and whether existing single-respondent institutional measures, typically obtained from IT or senior management informants, systematically over-represent one stratum of a differentiated phenomenon.

A quantitative test of the full model would require instruments for all six constructs, of which only C4 and, partially, C5 have established precedents. Developing and validating the remaining four is the obvious

next step, and the specification in Section 2.5 is offered with that use in mind.

As the implication, For university leadership, the findings indicate that AI should be planned at institutional rather than departmental level, with explicit attention to interoperability between platforms (C2); that interpretive training, not only operational training, should be resourced and treated as continuous (C4); and that cross-functional AI governance committees spanning leadership, academic units, IT, legal, and student affairs provide the visibility on which stakeholder trust depends (C5). For IT functions, the priority indicated is integration and explainability rather than capability expansion: systems whose outputs users cannot interpret generate limited managerial value regardless of analytical sophistication. For national policy, the findings support guidance establishing baseline expectations for data governance, transparency, and human oversight in higher education AI, consistent with the principles set out by Nguyen et al. (2023) and Jobin et al. (2019); funding for digital infrastructure to prevent capability divergence between better- and less-resourced institutions; and cross-institutional mechanisms for sharing implementation experience.

Six limitations bound these findings. First, the study examined two universities in a single Chinese province; the institutions were selected for advanced deployment and are not representative of the sector, and transferability to differently resourced or governed contexts should be established rather than assumed. Second, the sample of 15 interview participants and 10 focus group participants, while sufficient for saturation in phenomenological inquiry, cannot support claims about the

distribution of experience within the institutions. Third, the design is cross-sectional and captures a single moment in a rapidly moving field; the advisory settlement described in Section 5.5 may not be stable. Fourth, the qualitative design establishes how participants experience and interpret efficiency gains but does not measure them; the efficiency claims reported here are perceptual and warrant quantitative corroboration. Fifth, the six constructs are specified for qualitative inquiry as sensitising concepts; they have not been subjected to measurement development or validity testing, and the propositions in Section 2.6 are supported qualitatively but remain hypotheses rather than findings. Sixth, the propositions were not tested against disconfirming cases in a structured way; qualitative support for a proposed relationship is weaker evidence than its survival of a deliberate attempt at refutation, and the design did not include one.

7. Conclusion

This study examined how AI technologies are experienced, applied, and governed within the management systems of two Chinese universities, using six theoretically grounded constructs derived from systems, diffusion, human capital, institutional, and sociometrical perspectives. The evidence indicates that AI has passed from innovation to infrastructure at both sites: smart campus platforms, analytics dashboards, automated scheduling, chatbot services, and cloud analytics are described by participants as ordinary features of institutional work rather than as technologies under evaluation. Three findings qualify this account. Embedding is role-differentiated: the same institutional phenomenon presents differently to administrators, IT staff, faculty, and

students, which means institution-level characterizations of AI adoption obscure more than they reveal. Efficiency gains are real in participants' accounts but bounded by interpretive capability, locating the binding constraint in human capital rather than in system capability. And governance functions as a condition of value rather than as a constraint upon it, with trust tracking the visibility of safeguards. Across every instrument, institution, and role, AI was positioned as advisory. Participants described these systems as expanding what they could see about their

institutions while leaving unchanged who decides what to do about it. The phenomenon documented here is therefore not the automation of university management but its mediation, a reorganization of institutional information that leaves managerial accountability where it was. Whether that settlement holds as system capability advances is the question this line of research should take up next.

References

- Bandura, A. (1997). *Self-efficacy: The exercise of control*. W. H. Freeman.
- Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99–120. <https://doi.org/10.1177/014920639101700108>
- Bates, T., Cobo, C., Mariño, O., & Wheeler, S. (2020). Can artificial intelligence transform higher education? *International Journal of Educational Technology in Higher Education*, 17(1), Article 42. <https://doi.org/10.1186/s41239-020-00218-x>
- Becker, G. S. (1964). *Human capital: A theoretical and empirical analysis, with special reference to education*. National Bureau of Economic Research / Columbia University Press.
- Blumer, H. (1954). What is wrong with social theory? *American Sociological Review*, 19(1), 3–10. <https://doi.org/10.2307/2088165>
- Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S. W., & Siemens, G. (2024). A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour. *International Journal of Educational Technology in Higher Education*, 21(1), Article 4. <https://doi.org/10.1186/s41239-023-00436-z>
- Bowen, G. A. (2009). Document analysis as a qualitative research method. *Qualitative Research Journal*, 9(2), 27–40. <https://doi.org/10.3316/QRJ0902027>
- Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101. <https://doi.org/10.1191/1478088706qp063oa>
- Brynjolfsson, E., & McAfee, A. (2017, July 18). The business of artificial intelligence. *Harvard Business Review*. <https://hbr.org/2017/07/the-business-of-artificial-intelligence>
- Cath, C., Wachter, S., Mittelstadt, B., Taddeo, M., & Floridi, L. (2018). Artificial intelligence and the 'good society': The US, EU, and UK approach. *Science and Engineering Ethics*, 24(2), 505–528. <https://doi.org/10.1007/s11948-017-9901-7>
- Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. *Education and Information Technologies*, 25(5), 3443–3463. <https://doi.org/10.1007/s10639-020-10159-7>

-
- Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access*, 8, 75264–75278. <https://doi.org/10.1109/ACCESS.2020.2988510>
- Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1), 128–152. <https://doi.org/10.2307/2393553>
- Cooper, R. B., & Zmud, R. W. (1990). Information technology implementation research: A technological diffusion approach. *Management Science*, 36(2), 123–139. <https://doi.org/10.1287/mnsc.36.2.123>
- Creswell, J. W., & Poth, C. N. (2018). *Qualitative inquiry and research design: Choosing among five approaches* (4th ed.). Sage.
- Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education*, 20(1), Article 22. <https://doi.org/10.1186/s41239-023-00392-8>
- Daniel, B. (2015). Big data and analytics in higher education: Opportunities and challenges. *British Journal of Educational Technology*, 46(5), 904–920. <https://doi.org/10.1111/bjet.12230>
- Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108–116. <https://hbr.org/2018/01/artificial-intelligence-for-the-real-world>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems*, 19(4), 9–30. <https://doi.org/10.1080/07421222.2003.11045748>
- Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, 144(1), 114–126. <https://doi.org/10.1037/xge0000033>
- DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 48(2), 147–160. <https://doi.org/10.2307/2095101>
- Ferguson, R. (2012). Learning analytics: Drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, 4(5–6), 304–317. <https://doi.org/10.1504/IJTEL.2012.051816>
- Floridi, L., Cows, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B., Valcke, P., & Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines*, 28(4), 689–707. <https://doi.org/10.1007/s11023-018-9482-5>
- Gašević, D., Tsai, Y.-S., Dawson, S., & Pardo, A. (2019). How do we start? An approach to learning analytics adoption in higher education. *The International Journal of Information and Learning Technology*, 36(4), 342–353. <https://doi.org/10.1108/IJILT-02-2019-0024>
- George, B., & Wooden, O. (2023). Managing the strategic transformation of higher education through artificial intelligence. *Administrative Sciences*, 13(9), Article 196. <https://doi.org/10.3390/admsci13090196>
- Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, 19(2), 213–236. <https://doi.org/10.2307/249689>
- Gorry, G. A., & Scott Morton, M. S. (1971). A framework for management information systems. *Sloan Management Review*, 13(1), 55–70.
- Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field Methods*, 18(1), 59–82. <https://doi.org/10.1177/1525822X05279903>
-

- Ifenthaler, D., & Yau, J. Y.-K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development*, 68(4), 1961–1990. <https://doi.org/10.1007/s11423-020-09788-z>
- Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human–AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577–586. <https://doi.org/10.1016/j.bushor.2018.03.007>
- Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, 1(9), 389–399. <https://doi.org/10.1038/s42256-019-0088-2>
- Katsamakos, E., Pavlov, O. V., & Saklad, R. (2024). Artificial intelligence and the transformation of higher education institutions: A systems approach. *Sustainability*, 16(14), Article 6118. <https://doi.org/10.3390/su16146118>
- Katz, D., & Kahn, R. L. (1978). *The social psychology of organizations* (2nd ed.). Wiley.
- Khatri, V., & Brown, C. V. (2010). Designing data governance. *Communications of the ACM*, 53(1), 148–152. <https://doi.org/10.1145/1629175.1629210>
- Knox, J. (2020). Artificial intelligence and education in China. *Learning, Media and Technology*, 45(3), 298–311. <https://doi.org/10.1080/17439884.2020.1754236>
- Kuleto, V., Ilić, M., Dumangiu, M., Ranković, M., Martins, O. M. D., Păun, D., & Mihoreanu, L. (2021). Exploring opportunities and challenges of artificial intelligence and machine learning in higher education institutions. *Sustainability*, 13(18), Article 10424. <https://doi.org/10.3390/su131810424>
- Lebovitz, S., Lifshitz-Assaf, H., & Levina, N. (2022). To engage or not to engage with AI for critical judgments: How professionals deal with opacity when using AI for medical diagnosis. *Organization Science*, 33(1), 126–148. <https://doi.org/10.1287/orsc.2021.1549>
- Leonardi, P. M. (2011). When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies. *MIS Quarterly*, 35(1), 147–167. <https://doi.org/10.2307/23043493>
- Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry*. Sage.
- Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, 151, 90–103. <https://doi.org/10.1016/j.obhdp.2018.12.005>
- Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1–16). ACM. <https://doi.org/10.1145/3313831.3376727>
- Long, P., & Siemens, G. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review*, 46(5), 30–40. <https://er.educause.edu/articles/2011/9/penetrating-the-fog-analytics-in-learning-and-education>
- Mahroeian, H., & Daniel, B. (2021). Is New Zealand's higher education sector ready to employ analytics initiatives to enhance its decision-making process? *International Journal of Artificial Intelligence in Education*, 31(4), 940–979. <https://doi.org/10.1007/s40593-021-00243-5>
- Malone, T. W., & Crowston, K. (1994). The interdisciplinary study of coordination. *ACM Computing Surveys*, 26(1), 87–119. <https://doi.org/10.1145/174666.174668>
- Mandinach, E. B., & Gummer, E. S. (2016). What does it mean for teachers to be data literate: Laying out the skills, knowledge, and dispositions. *Teaching and Teacher Education*, 60, 366–376. <https://doi.org/10.1016/j.tate.2016.07.011>
- Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, 20(3), 709–734. <https://doi.org/10.2307/258792>
- Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Information technology and organizational performance: An integrative model of IT business value. *MIS Quarterly*, 28(2), 283–322. <https://doi.org/10.2307/25148636>

- Meyer, J. W., & Rowan, B. (1977). Institutionalized organizations: Formal structure as myth and ceremony. *American Journal of Sociology*, 83(2), 340–363. <https://doi.org/10.1086/226550>
- Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, 58(3), Article 103434. <https://doi.org/10.1016/j.im.2021.103434>
- Mintzberg, H. (1973). *The nature of managerial work*. Harper & Row.
- Molina-Carmona, R., & García-Peñalvo, F. J. (2024). Safeguarding knowledge: Ethical artificial intelligence governance in the university digital transformation. In *Advanced technologies and the university of the future* (pp. 201–220). Springer. https://doi.org/10.1007/978-3-031-52296-4_10
- Moustakas, C. (1994). *Phenomenological research methods*. Sage.
- Nguyen, A., Ngo, H. N., Hong, Y., Dang, B., & Nguyen, B.-P. T. (2023). Ethical principles for artificial intelligence in education. *Education and Information Technologies*, 28(4), 4221–4241. <https://doi.org/10.1007/s10639-022-11316-w>
- Okonkwo, C. W., & Ade-Ibijola, A. (2021). Chatbots applications in education: A systematic review. *Computers and Education: Artificial Intelligence*, 2, Article 100033. <https://doi.org/10.1016/j.caeai.2021.100033>
- Orlikowski, W. J. (2000). Using technology and constituting structures: A practice lens for studying technology in organizations. *Organization Science*, 11(4), 404–428. <https://doi.org/10.1287/orsc.11.4.404.14600>
- Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics—Part A: Systems and Humans*, 30(3), 286–297. <https://doi.org/10.1109/3468.844354>
- Pasquale, F. (2015). *The black box society: The secret algorithms that control money and information*. Harvard University Press.
- Patton, M. Q. (2015). *Qualitative research and evaluation methods* (4th ed.). Sage.
- Polin, K., Yigitcanlar, T., Limb, M., & Washington, T. (2023). The making of smart campus: A review and conceptual framework. *Buildings*, 13(4), Article 891. <https://doi.org/10.3390/buildings13040891>
- Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.
- Scott, W. R. (2014). *Institutions and organizations: Ideas, interests, and identities* (4th ed.). Sage.
- Selwyn, N. (2019). *Should robots replace teachers? AI and the future of education*. Polity Press.
- Selwyn, N. (2021). *Education and technology: Key issues and debates* (3rd ed.). Bloomsbury.
- Shneiderman, B. (2020). Human-centered artificial intelligence: Reliable, safe & trustworthy. *International Journal of Human–Computer Interaction*, 36(6), 495–504. <https://doi.org/10.1080/10447318.2020.1741118>
- Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, 69(1), 99–118. <https://doi.org/10.2307/1884852>
- Smith, J. A., Flowers, P., & Larkin, M. (2009). *Interpretative phenomenological analysis: Theory, method and research*. Sage.
- State Council of the People's Republic of China. (2017). *New generation artificial intelligence development plan* (Guo Fa [2017] No. 35).
- Strauss, A., & Corbin, J. (1998). *Basics of qualitative research: Techniques and procedures for developing grounded theory* (2nd ed.). Sage.
- Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509–533. [https://doi.org/10.1002/\(SICI\)1097-0266\(199708\)18:7<509::AID-SMJ882>3.0.CO;2-Z](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z)

- Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.
- Tsai, Y.-S., Poquet, O., Gašević, D., Dawson, S., & Pardo, A. (2019). Complexity leadership in learning analytics: Drivers, challenges and opportunities. *British Journal of Educational Technology*, 50(6), 2839–2854. <https://doi.org/10.1111/bjet.12846>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- von Bertalanffy, L. (1968). *General system theory: Foundations, development, applications*. George Braziller.
- Wang, Y., Liu, C., & Tu, Y.-F. (2021). Factors affecting the adoption of AI-based applications in higher education: An analysis of teachers' perspectives using structural equation modeling. *Educational Technology & Society*, 24(3), 116–129.
- Weill, P., & Ross, J. W. (2004). *IT governance: How top performers manage IT decision rights for superior results*. Harvard Business School Press.
- Williamson, B., & Eynon, R. (2020). Historical threads, missing links, and future directions in AI in education. *Learning, Media and Technology*, 45(3), 223–235. <https://doi.org/10.1080/17439884.2020.1798995>
- Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—Where are the educators? *International Journal of Educational Technology in Higher Education*, 16(1), Article 39. <https://doi.org/10.1186/s41239-019-0171-0>
- Zuboff, S. (1988). *In the age of the smart machine: The future of work and power*. Basic Books.