AI-Based Information Systems Adoption in University Administration: A Multidimensional Readiness Model

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ABSTRACT

Artificial intelligence (AI) can improve efficiency, service delivery, and decision making in university administration, yet implementation is hindered by the lack of readiness frameworks designed for administrative contexts. This theoretical review synthesizes fragmented knowledge on readiness for adopting AI-based information systems (AI-IS) in university administration. Drawing on the Technology–Organization–Environment framework, the Technology Readiness Index, and Resource Dependence Theory, it proposes an integrated model of individual, technological, organizational, and environmental readiness. Following Jaakkola's (2020) theory synthesis approach with a documented search process, the review identifies three gaps: limited attention to administrative applications, the absence of AI-specific readiness constructs, and the lack of validated instruments. In response, twenty propositions, including moderating and mediating effects, are developed for empirical testing in Saudi higher education. The study extends established frameworks with AI-specific constructs (algorithmic trust, data governance, and ethical AI governance) and offers a basis for readiness diagnostics for university administrators and policymakers.

Keywords: Artificial Intelligence, Information Systems, Readiness Model, University Administration, Technology Adoption, Theoretical Review.

INTRODUCTION

AI-Based Information Systems (AI-IS), enhanced by machine learning, natural language processing, and predictive analytics, can modernize university administration by automating routine tasks and supporting admissions, resource allocation, student services, and finance (Khairullah et al., 2025).

Yet AI-IS adoption in university administration remains limited and fragmented (Al-Zahrani & Alasmari, 2025), partly because comprehensive readiness frameworks to guide institutional planning are lacking (Uren & Edwards, 2023). Readiness for AI is multidimensional, spanning individual, technological, organizational, and environmental factors (Felemban et al., 2024; Jöhnk et al., 2021), but the Technology Acceptance Model (TAM), Diffusion of Innovation (DOI) theory, and the TOE framework were developed for traditional information systems and do not account for algorithmic trust, data governance, ethics, or the probabilistic nature of AI outputs.

Moreover, AI research in higher education has focused on teaching and learning, with little attention to admissions, finance, human resources, and registrar services (Al-Zahrani & Alasmari, 2025), although these functions are foundational to institutional performance.

This review focuses on Saudi higher education, where Vision 2030 and the National Strategy for Data and AI (SDAIA, 2020) make AI a national priority. Recent reviews confirm that AI research in higher education still centres on teaching and learning rather than administration (Zawacki-Richter et al., 2019; Crompton & Burke, 2023; Bond et al., 2024).

This paper addresses these gaps through a theoretical review that proposes a readiness model tailored to university administration. It makes three contributions: it assigns TOE, TRI, and RDT distinct explanatory roles rather than aggregating their factors; it locates three AI-specific constructs (algorithmic trust, data governance, and ethical AI governance) in the model; and it specifies environmental readiness as a moderator and AI-IS adoption as a mediator. Practically, it provides a basis for developing a validated readiness instrument.

The review addresses four questions: (RQ1) Which readiness dimensions influence AI-IS adoption in university administration? (RQ2) Which theoretical frameworks have been applied, and what are their limitations in administrative contexts? (RQ3) What research gaps exist? (RQ4) How can a multidimensional readiness model be conceptualized to guide AI-IS adoption?

THEORETICAL FOUNDATIONS

Evolution of Information Systems and AI Characteristics

Information Systems (IS) have evolved from centralized data processing to intelligent, adaptive platforms (Kadry, 2014). AI differs from traditional, rule-based IS in three ways that reshape readiness requirements: it is probabilistic, producing outputs with confidence scores rather than fixed answers (Yadav & Mishra, 2024); it learns over time, making post-implementation governance as important as planning; and it is opaque, so even developers may not fully explain an output (Zednik, 2021). These characteristics demand algorithmic literacy, robust data governance, and trust calibration that traditional IS adoption models were not designed to address.

AI-Based Information Systems in Administrative Domains

AI-IS in universities include chatbots for student and staff queries, predictive analytics for admissions and enrollment, automated document processing for finance and human resources, and decision support for resource planning (Narne et al., 2024). AI is also seen as a driver of strategic change in university management (George & Wooden, 2023).

These systems can automate repetitive tasks and improve the speed and accuracy of decisions, but they may perpetuate biases in historical data (Ntoutsi et al., 2020), and their decisions are not easily interpretable (Camilleri, 2024). Readiness assessment for AI-IS must therefore address data governance, ethics, user trust, and human oversight.

The Concept of Readiness for Technology Adoption

Readiness is the extent to which individuals, organizations, and infrastructures are prepared to implement an innovation (Felemban et al., 2024; Uren & Edwards, 2023). It is usually conceptualized at four levels: individual (digital literacy, confidence, openness to change, perceived usefulness; Falebita & Kok, 2025), technological (infrastructure, integration, data quality, cybersecurity; Uren & Edwards, 2023), organizational (policies, leadership, resources, innovation culture; Felemban et al., 2024), and environmental (government policy, competition, regulation; Zhang et al., 2020).

THEORETICAL MODELS AND FRAMEWORKS

Technology Acceptance Model

TAM holds that perceived usefulness and ease of use shape attitudes and intention to use a system (Davis, 1989); its extensions (TAM2, TAM3, UTAUT) add social influence and facilitating conditions (Venkatesh et al., 2003). In higher education it has explained adoption of e-learning and, recently, of AI by faculty and students. However, TAM is individual-centric: it ignores organizational and technological readiness, institutional factors such as leadership and policy (Felemban et al., 2024), and AI-specific issues such as algorithmic trust and governance (Camilleri, 2024).

Diffusion of Innovation Theory

DOI explains how innovations spread through a social system according to relative advantage, compatibility, complexity, trialability, and observability, with adopters ranging from innovators to laggards (Rogers et al., 2014). It has been applied to learning management systems and e-learning but offers no mechanism for assessing readiness across levels and does not address the ethical and regulatory complexities of AI.

Technology-Organization-Environment Framework

TOE holds that adoption is shaped by technological, organizational, and environmental contexts (Tornatzky & Fleischer, 1990), making it useful for AI because it covers internal and external factors. In Saudi organizations, Felemban et al. (2024) found government support, leadership commitment, and employee readiness to be key determinants. However, TOE classifies factors without AI-specific measures of data governance, ethics, or transparency (Bin-Nashwan et al., 2025) and gives little guidance on individual readiness.

Resource Dependence Theory

Resource Dependence Theory (RDT) explains how organizations manage external dependencies and secure critical resources (Pfeffer & Salancik, 1978). Universities depend on government funding, partnerships, and collaborations for AI resources, giving external stakeholders influence over their decisions (Hillman et al., 2009). RDT, however, says little about internal readiness such as culture, ethics, and staff acceptance (Felemban et al., 2024), or about the risks of vendor dependence.

Technology Readiness Index

The Technology Readiness Index (TRI) captures individuals' optimism, innovativeness, discomfort, and insecurity toward technology (Parasuraman, 2000). It has mainly been applied, often with TAM, to student and faculty acceptance of learning technologies, overlooking organizational and environmental factors and administrative staff.

Socio-Technical and Institutional Perspectives

Socio-technical systems theory emphasizes joint optimization of social and technical subsystems (Bostrom & Heinen, 1977), balancing technological sophistication with staff readiness. This perspective underpins the mediating role of adoption (Section 4.5).

Institutional theory explains adoption through coercive (e.g., government mandates), mimetic (e.g., rankings), and normative (professional standards) pressures (DiMaggio & Powell, 1983). Coercive pressure informs the moderating role of environmental readiness (Section 4.5).

Limitations of Existing Models

Existing models therefore address only fragments of readiness: TAM emphasizes perceptions, DOI diffusion processes, TOE categorizes influences without operational metrics, and TRI captures psychological readiness only. Most were developed for traditional IS and omit AI-specific concerns such as algorithmic trust, bias, data governance, and transparency, and higher-education applications focus on faculty and students rather than administrative staff.

Critically, these frameworks differ mainly in level of analysis: TAM, DOI, and TRI explain individual acceptance, TOE explains organizational decisions, and RDT explains external dependence. Recent integrations (Abulail et al., 2025; Bin-Nashwan et al., 2025) combine them additively, without explaining how levels interact or how readiness becomes performance. Section 4.5 addresses this gap.

METHODOLOGY

Research Design

This study uses a theoretical review, following Jaakkola's (2020) theory synthesis guidelines, to develop a readiness model for AI-IS adoption in university administration. This approach suits theory building in a nascent, multidisciplinary field where meta-analysis is not feasible. The review followed four iterative steps: descriptive mapping, thematic synthesis, theoretical integration, and model development with corresponding propositions. The analytical trail is reported in Figure 1 and Tables 2–3.

Literature Search Strategy

Scopus, Web of Science, Google Scholar, IEEE Xplore, and ACM Digital Library were searched for peer-reviewed articles, conference papers, and dissertations published from 2015 to 2025, combining ("artificial intelligence" OR "AI" OR "machine learning") AND ("readiness" OR "adoption" OR "implementation") AND ("university administration" OR "higher education" OR "organizational"). Forward and backward citation tracking of seminal works (Tornatzky & Fleischer, 1990; Davis, 1989; Parasuraman, 2000; Rogers et al., 2014) was used to identify further theory-relevant sources. The screening process is shown in Figure 1 (adapted from PRISMA 2020; Page et al., 2021).

Selection Criteria

Studies were included if they (a) addressed technology adoption or readiness in organizations; (b) examined individual, technological, organizational, or environmental factors; (c) were relevant to higher education or university administration; and (d) contributed theory or evidence on readiness. Studies focused only on teaching and learning, on non-AI technologies without transferable insights, or lacking theoretical grounding were excluded. Conceptual relevance was emphasized over formal quality scoring (Templier & Paré, 2015).

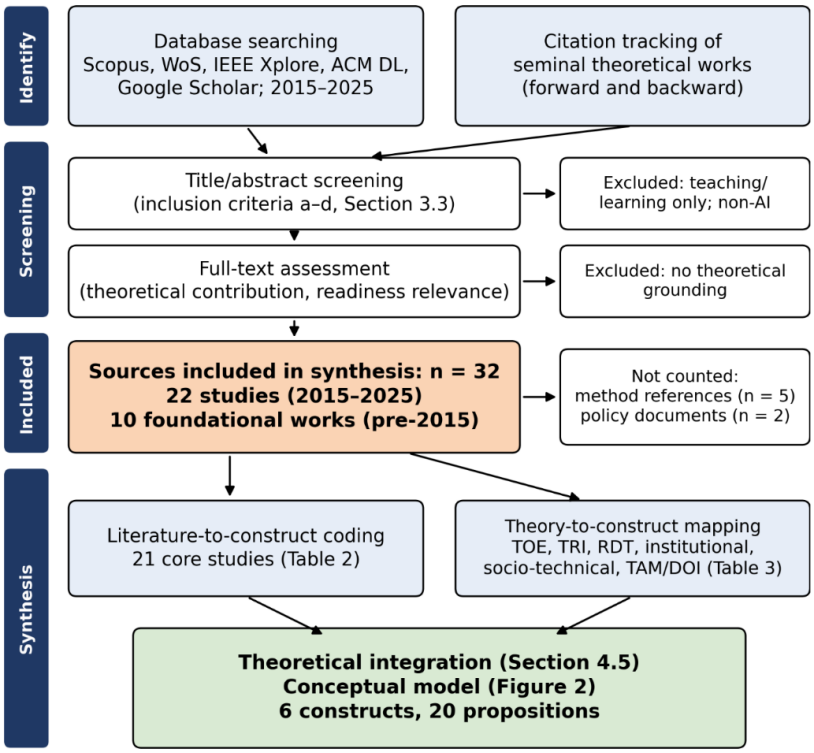


Figure 1. Search, screening and synthesis flow (adapted from PRISMA 2020; Page et al., 2021)

In total, 32 sources were included: 22 studies from 2015–2025 and 10 foundational theoretical works identified through citation tracking. Methodological references (n = 5) and policy documents (n = 2) were not counted. The 21 core studies are mapped in Table 2.

Data Analysis and Theory Synthesis

Analysis proceeded in four iterative steps. First, studies were coded for frameworks, constructs, findings, and limitations. Second, readiness factors were coded line by line and grouped into descriptive and analytical themes (Thomas & Harden, 2008). Third, themes were mapped against TOE, TRI, RDT, TAM, and DOI; overlapping constructs were integrated and AI-specific concepts (e.g., algorithmic trust, data governance) added. Fourth, the integrated constructs and their proposed relationships were represented in a conceptual model, from which research propositions were derived. Steps two and three are reported in Table 2 (literature-to-construct matrix) and Table 3 (theory-to-construct mapping). Of the 32 included sources, 21 core studies were selected for detailed literature-to-construct mapping based on their direct relevance to the proposed readiness dimensions, while the remaining sources primarily supported theoretical foundations and contextual interpretation.

Rigor and Trustworthiness

Established criteria for conceptual research were applied (Lincoln & Guba, 1985; Jaakkola, 2020). Credibility rests on multi-database searching and iterative comparison with sources, transferability on articulating propositions for testing across university contexts, and dependability was supported by the documented search, screening flow (Figure 1), and coding outputs (Tables 2–3). Confirmability rests on deriving the model from the literature rather than a priori assumptions. Conceptual saturation was judged to be reached when further sources yielded no new readiness dimensions or frameworks. This judgement is interpretive.

FINDINGS

Readiness Dimensions for AI-IS Adoption

For AI-IS in university administration, four core dimensions emerge consistently across the included studies (Table 2).

Individual readiness covers staff digital literacy, AI competence, attitudes, trust, optimism, and innovativeness (Davis, 1989; Laupichler et al., 2023; Bedué & Fritzsche, 2022; Karam & Abou, 2025; Parasuraman, 2000).

Technological readiness concerns IT infrastructure, data governance, interoperability, and AI platform capability (Bin-Nashwan et al., 2025; Felemban et al., 2024; Chotia et al., 2025).

Organizational readiness encompasses leadership, strategic alignment, resources, innovation culture, and ethical governance (Felemban et al., 2024; Khairullah et al., 2025; Camilleri, 2024).

Environmental readiness includes government policy and regulation, competitive pressure, funding, and external expertise (Felemban et al., 2024). The model retains government support, policy and regulatory clarity, and external funding (Section 5.2).

Theoretical Frameworks and Their Application

Table 1 summarizes the limitations of the main frameworks in AI-IS contexts.

Table 1. Summary of Theoretical Frameworks and Limitations

Model	Limitations in AI-IS Context	Key Sources
TAM	Ignores organizational and technological readiness; does not address ethical or governance aspects of AI	Davis (1989); Abulail et al. (2025)
DOI	Lacks readiness evaluation; limited attention to AI-specific issues such as transparency and ethics	Rogers et al. (2014)
TOE	Lacks focus on individual readiness; limited metrics for AI	Tornatzky & Fleischer (1990);

	governance and ethical readiness	Felemban et al. (2024)
RDT	Neglects internal culture, staff acceptance, and readiness dimensions	Pfeffer & Salancik (1978); Hillman et al. (2009)
TRI	Limited to individual factors; overlooks organizational and environmental influences	Parasuraman (2000)

Table 2. Literature-to-construct synthesis matrix (core studies)

Study	Context / design	Lens	Readiness factors extracted	Model construct (proposition)
Felemban et al. (2024)	Saudi organizations; empirical	TOE	Government support, leadership, employee resistance	Environmental readiness (P4); leadership (P3a); attitude (P2b)
Uren & Edwards (2023)	Organizations; empirical	Technology readiness	People, process and data readiness	IT infrastructure (P1a); data governance (P1b); AI competence (P2a)
Jöhnk et al. (2021)	Organizations; interviews	Organizational AI readiness	Strategy, resources, knowledge, culture	P3b; P3c; P3d
Bin-Nashwan et al. (2025)	Finance/auditing; SEM	TOE–TAM–RDT	Big data governance; external dependence	Data governance (P1b); moderation logic (P4)
Chotia et al. (2025)	Start-ups; empirical	AI capabilities	AI infrastructure readiness	Cloud-based data infrastructure (P1c); AI platform capability (P1d)
Laupichler et al. (2023)	Non-experts; scale development	AI literacy	AI literacy	AI competence (P2a); digital literacy (P2d)
Bedué & Fritzsche (2022)	Organizations; empirical	Trust	Trust requirements for AI	Algorithmic trust (P2c)
Falebita & Kok (2025)	University students; PLS-SEM	TAM / technology readiness	Readiness, self-efficacy, attitude	Attitude (P2b); AI competence (P2a)
Karam & Abou (2025)	Digital transformation	Change management	Resistance to change	Attitude (P2b)
Camilleri (2024)	Conceptual review	AI governance	Accountability, transparency, bias	Ethical AI governance (P3e)
Ntoutsi et al. (2020); Zednik (2021)	Conceptual	Bias; explainable AI	Data bias; opacity	Data governance (P1b); algorithmic trust (P2c)
Khairullah et al. (2025)	Higher education administration	Strategic leadership	Responsible AI leadership	Leadership (P3a); strategic alignment (P3b)
George & Wooden (2023)	Higher education management; conceptual	Strategic transformation	AI-enabled administrative change	Strategic alignment (P3b); performance link (P5)
Narne et al. (2024)	Management decision support	Decision support systems	AI-supported decision quality	Administrative performance (P5)
Abulail et al. (2025)	Higher education; SEM	DOI–TOE–TAM	Integrated adoption factors	Attitude (P2b); additive-model critique (Sec. 2.5)
Zhang et al. (2020)	Green innovation; empirical	TOE readiness	Environmental readiness	Environmental readiness (P4)
Al-Zahrani & Alasmari (2025)	MENA higher education; review	—	Adoption strategies and challenges	Context; environmental readiness (P4)
Zawacki-Richter et al. (2019); Crompton & Burke (2023); Bond et al. (2024)	Higher education; systematic reviews	—	Teaching/learning focus; ethics gap	Gap 1; ethical AI governance (P3e)

Prior AI Readiness Models

Felemban et al. (2024) identified government and leadership support as the strongest enablers of AI adoption and employee resistance as a major barrier; Uren and Edwards (2023) showed that readiness in people, processes, and data matters as much as technology; and Jöhnk et al. (2021) stressed continuous assessment of organizational AI readiness. However, these models are largely additive and rarely explain how factors interact or how readiness becomes performance.

Research Gaps

The synthesis reveals six gaps:

1. Most studies emphasize pedagogy and research, while administrative functions receive comparatively little attention (Zawacki-Richter et al., 2019; Crompton & Burke, 2023).

2. Readiness measures lack AI-specific constructs such as algorithmic trust, data governance, and model lifecycle management (Bedué & Fritzsche, 2022; Bin-Nashwan et al., 2025).

3. No framework integrates individual, technological, organizational, and environmental dimensions for administrative AI-IS adoption (Davis, 1989; Rogers et al., 2014; Tornatzky & Fleischer, 1990).

4. Empirical evidence on administrative preparedness is scarce.

5. Few validated, context-specific instruments exist; most are adapted from generic IS models.

6. Foundational models were developed in private-sector contexts and overlook the shared governance, multi-stakeholder accountability, and risk-averse cultures of universities.

Theoretical Integration and Explanatory Mechanisms

Rather than aggregating dimensions, the synthesis assigns each theory a distinct role, yielding four mechanisms (Table 3).

Multi-level complementarity (TOE + TRI). TOE covers institutional capacity but not individuals; TRI covers individuals but not institutions. Adoption requires both, so the three internal dimensions are complementary antecedents (P1–P3).

Trust calibration (TRI + AI characteristics). Because AI outputs are probabilistic and opaque (Zednik, 2021), TRI's insecurity is reframed as algorithmic trust (Bedué & Fritzsche, 2022), supported by data governance and ethical AI governance.

Resource-contingent conversion (RDT + institutional theory). Public universities depend on government for funding and legitimacy (Pfeffer & Salancik, 1978). External support cannot create adoption without internal capacity, but it strengthens the conversion of internal readiness into adoption by reducing resource constraints and regulatory uncertainty (DiMaggio & Powell, 1983). Environmental readiness is therefore a moderator (P4a–P4c), not a direct predictor.

Capability-to-value (socio-technical theory). Readiness is a capacity; performance gains occur only when AI-IS are routinely used in workflows (George & Wooden, 2023). Adoption is therefore a mediator (P5, P6a–P6c).

Table 3. Theory-to-construct mapping

Theory	Logic borrowed	Model construct(s)	Propositions	Contribution
TOE (Tornatzky &	Technological,	Technological,	P1, P3, P4	Structural categories;

Fleischer, 1990)	organizational, environmental contexts	organizational, environmental readiness		extended with AI-specific facets
TRI (Parasuraman, 2000)	Optimism, innovativeness, discomfort, insecurity	Individual readiness	P2	Adds the individual level; insecurity reframed as algorithmic trust
RDT (Pfeffer & Salancik, 1978)	Dependence on external resources	Environmental readiness (moderator)	P4a–P4c	Resource-contingent conversion
Institutional theory (DiMaggio & Powell, 1983)	Coercive pressure	Policy and regulatory clarity	P4a–P4c	Reduces regulatory uncertainty
Socio-technical theory (Bostrom & Heinen, 1977)	Joint optimization of social and technical subsystems	AI-IS adoption (mediator)	P5, P6a–P6c	Capability-to-value
TAM / DOI (Davis, 1989; Rogers et al., 2014)	Usefulness, ease of use	Attitude indicators	P2b	Indicator sources only

Proposed Multidimensional Readiness Model

Conceptual Model

Building on the synthesis, the proposed model is shown in Figure 2.

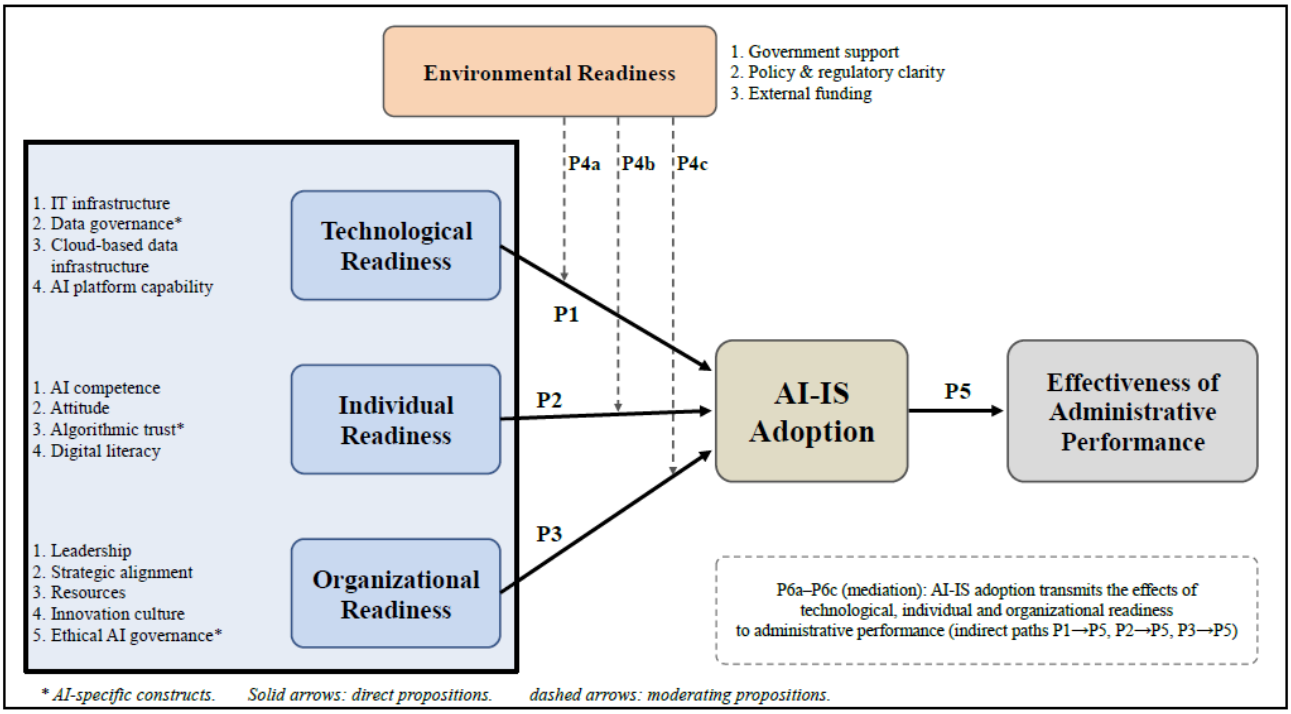


Figure 2. Conceptual Model of AI-IS Readiness in University Administration

The model depicts three internal readiness dimensions as independent variables: Technological Readiness (IT infrastructure, data governance, cloud-based data infrastructure, AI platform capability), Individual Readiness (AI competence, attitude, algorithmic trust, digital literacy), and Organizational Readiness (leadership, strategic alignment, resources, innovation culture, ethical AI governance). Environmental Readiness (government support, policy and regulatory clarity, external funding) is positioned as a moderator (P4a–P4c). AI-IS Adoption (acceptance, integration, and routinization) serves as a mediator (P6a–P6c), and Effectiveness of Administrative Performance (process efficiency, decision quality, service responsiveness) is the outcome variable. AI-specific constructs are marked (*) in Figure 2.

Definition of Constructs

1. Technological readiness is the maturity of IT infrastructure, interoperability, cybersecurity, data governance (quality, privacy, bias mitigation, and compliance; Bin-Nashwan et al., 2025), and AI platform capability to deploy, monitor, and update models (Uren & Edwards, 2023; Chotia et al., 2025). Cloud-based data infrastructure is an indicator of technological readiness, not a separate dimension; it is listed separately because AI-IS need scalable computing and consolidated data that legacy systems rarely provide (Chotia et al., 2025).

2. Individual readiness reflects staff AI competence and digital literacy, including the ability to evaluate AI outputs critically (Laupichler et al., 2023); algorithmic trust, i.e., confidence in probabilistic, sometimes opaque outputs (Bedué & Fritzsche, 2022); and attitude, including perceived usefulness and openness to change. Following TRI, optimism and innovativeness are captured in attitude, and insecurity in algorithmic trust.

3. Organizational readiness comprises leadership and strategic alignment (Felemban et al., 2024), resources, an innovation culture tolerant of experimentation, and ethical AI governance covering bias accountability, transparency, and vendor management. Ethical AI governance is organizational because it concerns policies, oversight, and accountability for AI decisions (Camilleri, 2024); data governance concerns data quality, privacy, and security.

4. Environmental readiness covers external factors that shape institutional capacity and impetus for adoption. It is narrowed to three facets: government support, policy and regulatory clarity, and external funding. Competitive pressure and external expertise are excluded as less relevant to public universities.

5. AI-IS adoption is the extent to which AI-IS are accepted, integrated, and routinized in administrative workflows. It mediates because performance gains require routine use (Section 4.5).

6. Effectiveness of administrative performance captures gains in process efficiency, decision quality, and service responsiveness resulting from AI-IS use.

Research Propositions

Based on the conceptual model, the following propositions are advanced:

Proposition 1 (Technological Readiness): Technological readiness positively influences AI-IS adoption in university administration. This relationship is manifested through:

- P1a: IT infrastructure positively influences adoption.
- P1b: Data governance positively influences adoption.
- P1c: Cloud-based data infrastructure positively influences adoption.
- P1d: AI platform capability positively influences adoption.

Proposition 2 (Individual Readiness): Individual readiness positively influences AI-IS adoption in university administration. This relationship is manifested through:

- P2a: AI competence positively influences adoption.
- P2b: Attitude positively influences adoption.
- P2c: Algorithmic trust positively influences adoption.
- P2d: Digital literacy positively influences adoption.

Proposition 3 (Organizational Readiness): Organizational readiness positively influences AI-IS adoption in university administration. This relationship is manifested through:

- P3a: Leadership positively influences adoption.
- P3b: Strategic alignment positively influences adoption.
- P3c: Resources positively influence adoption.
- P3d: Innovation culture positively influences adoption.
- P3e: Ethical AI governance positively influences adoption.

Proposition 4 (Moderating Effect): Environmental readiness positively moderates the relationships between internal readiness dimensions and AI-IS adoption:

- P4a: Environmental readiness positively moderates the relationship between technological readiness and AI-IS adoption.
- P4b: Environmental readiness positively moderates the relationship between individual readiness and AI-IS adoption.
- P4c: Environmental readiness positively moderates the relationship between organizational readiness and AI-IS adoption.

Proposition 5 (Adoption–Performance Link): AI-IS adoption has a significant positive effect on Effectiveness of Administrative Performance.

Proposition 6 (Mediating Effect): AI-IS adoption mediates the relationships between internal readiness and administrative performance:

- P6a: AI-IS adoption mediates the effect of technological readiness on performance.
- P6b: AI-IS adoption mediates the effect of individual readiness on performance.
- P6c: AI-IS adoption mediates the effect of organizational readiness on performance.

Future Empirical Operationalization

Future empirical studies may operationalize the readiness dimensions using validated multi-item scales adapted to university administration. The proposed direct, moderating, and mediating relationships can be examined using structural equation modeling (SEM), subject to appropriate assessment of measurement reliability and validity.

DISCUSSION AND IMPLICATIONS

Theoretical Contributions

The model synthesizes TOE, TRI, and RDT, combining organizational and psychological levels of readiness, with each theory assigned a distinct explanatory role (Section 4.5). It introduces AI-specific constructs largely absent from traditional IS studies: algorithmic trust, data governance, and ethical AI governance (Bedué & Fritzsche, 2022; Bin-Nashwan et al., 2025; Camilleri, 2024). Positioning environmental readiness as a moderator rather than a direct predictor clarifies how external pressures interact with internal capabilities, extending institutional theory. Finally, the model reflects the socio-technical nature of AI-IS adoption, formalized through its mediating role, showing that sophisticated platforms without staff literacy and trust lead to underutilization.

Practical Implications

The model offers administrators a conceptual basis for a diagnostic tool for moving beyond isolated AI pilots. By structuring readiness across individual, technological, and organizational domains, it can guide targeted investment in staff training, infrastructure, or strategic alignment before large-scale adoption. Early identification of readiness gaps may help institutions reduce implementation risk, and involving staff in assessments can reduce resistance. Its indicators are candidate measurement items; a validated instrument must be developed before the model is used to prioritize investments.

Policy Implications

The model supports national digital transformation agendas, such as Saudi Vision 2030, by providing theory-informed recommendations on funding, regulation, and capacity building. Policies promoting AI literacy training, data governance standards, and ethical AI guidance (SDAIA, 2023) can accelerate institutional adoption, and the model may also inform other public-sector contexts.

CONCLUSION

This review identified the dimensions, frameworks, and gaps in research on AI-IS adoption readiness in university administration and proposed a model integrating individual, technological, organizational, and environmental readiness, with AI-specific constructs (algorithmic trust, data governance, and ethical AI governance) that distinguish it from traditional IS adoption frameworks. Successful adoption requires investment not only in infrastructure but also in staff development, strategic alignment, ethical governance, and environmental engagement. The twenty propositions (P1a–P6c) provide a foundation for empirical validation and for developing a validated readiness instrument. The review has limitations. The model is conceptual and requires validation through large-scale surveys and structural equation modeling, including tests of moderation and mediation. The synthesis is interpretive and bounded to 2015–2025. Cross-cultural and longitudinal studies are needed to test transferability and how readiness evolves during implementation, and future research should examine trust formation, resistance to AI, and actual organizational outcomes. The model nonetheless offers a basis for assessment, planning, and implementation as universities navigate AI integration.

REFERENCES

1. Abulail, R. N., Badran, O. N., Shkoukani, M. A., & Omeish, F. (2025). Exploring the factors influencing AI adoption intentions in higher education: An integrated model of DOI, TOE, and TAM. Computers, 14(6), 230. https://doi.org/10.3390/computers14060230
2. Al-Zahrani, A. M., & Alasmari, T. M. (2025). A comprehensive analysis of AI adoption, implementation strategies, and challenges in higher education across the Middle East and North Africa (MENA) region. Education and Information Technologies, 1–51. https://doi.org/10.1007/s10639-024-13300-y
3. Bedué, P., & Fritzsche, A. (2022). Can we trust AI? An empirical investigation of trust requirements and guide to successful AI adoption. Journal of Enterprise Information Management, 35(2), 530–549. https://doi.org/10.1108/JEIM-06-2020-0233
4. Bin-Nashwan, S. A., Li, J. Z., Jiang, H., Bajary, A. R., & Ma'aji, M. M. (2025). Does AI adoption redefine financial reporting accuracy, auditing efficiency, and information asymmetry? An integrated model of TOE-TAM-RDT and big data governance. Computers in Human Behavior Reports, 17, 100572. https://doi.org/10.1016/j.chbr.2024.100572
5. 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, 4. https://doi.org/10.1186/s41239-023-00436-z
6. Bostrom, R. P., & Heinen, J. S. (1977). MIS problems and failures: A socio-technical perspective. Part I: The causes. MIS Quarterly, 1(3), 17–32. https://doi.org/10.2307/248710

7. Camilleri, M. A. (2024). Artificial intelligence governance: Ethical considerations and implications for social responsibility. Expert Systems, 41(7), e13406. https://doi.org/10.1111/exsy.13406
8. Chotia, V., Sharma, P., Alshaghdali, N. O., Galgotia, D., & Sahore, N. (2025). Harnessing AI capabilities for startup scalability: Unlocking potential through AI-driven innovation ecosystems and AI-infrastructure readiness. European Journal of Innovation Management, 1–38. https://doi.org/10.1108/EJIM-03-2025-0397
9. Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. International Journal of Educational Technology in Higher Education, 20, 22. https://doi.org/10.1186/s41239-023-00392-8
10. 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
11. 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
12. Falebita, O. S., & Kok, P. J. (2025). Artificial intelligence tools usage: A structural equation modeling of undergraduates' technological readiness, self-efficacy and attitudes. Journal for STEM Education Research, 8(2), 257–282. https://doi.org/10.1007/s41979-024-00132-1
13. Felemban, H., Sohail, M., & Ruikar, K. (2024). Exploring the readiness of organisations to adopt artificial intelligence. Buildings, 14(8), 2460. https://doi.org/10.3390/buildings14082460
14. George, B., & Wooden, O. (2023). Managing the strategic transformation of higher education through artificial intelligence. Administrative Sciences, 13(9), 196. https://doi.org/10.3390/admsci13090196
15. Hillman, A. J., Withers, M. C., & Collins, B. J. (2009). Resource dependence theory: A review. Journal of Management, 35(6), 1404–1427. https://doi.org/10.1177/0149206309343469
16. Jaakkola, E. (2020). Designing conceptual articles: Four approaches. AMS Review, 10(1), 18–26. https://doi.org/10.1007/s13162-020-00161-0
17. Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes—An interview study of organizational AI readiness factors. Business & Information Systems Engineering, 63(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7
18. Kadry, S. (2014). On the evolution of information systems. In Systems theory: Perspectives, applications and developments (Vol. 1, pp. 197–208). Nova Science Publishers.
19. Karam, E., & Abou, B. (2025). AI-powered assessment of resistance to change in the context of digital transformation. International Journal of Advanced Computer Science and Applications, 16(6). https://doi.org/10.14569/IJACSA.2025.0160653
20. Khairullah, S. A., Harris, S., Hadi, H. J., Sandhu, R. A., Ahmad, N., & Alshara, M. A. (2025). Implementing artificial intelligence in academic and administrative processes through responsible strategic leadership in the higher education institutions. Frontiers in Education, 10, 1548104. https://doi.org/10.3389/feduc.2025.1548104
21. Laupichler, M. C., Aster, A., Haverkamp, N., & Raupach, T. (2023). Development of the "Scale for the assessment of non-experts' AI literacy"—An exploratory factor analysis. Computers in Human Behavior Reports, 12, 100338. https://doi.org/10.1016/j.chbr.2023.100338
22. Lincoln, Y. S., & Guba, E. G. (1985). Naturalistic inquiry. Sage Publications.
23. Narne, S., Dodda, S., Adedoja, T., Ayyalasomayajula, M. M. T., & Chintala, S. (2024). AI-driven decision support systems in management: Enhancing strategic planning and execution. International Journal on Recent and Innovation Trends in Computing and Communication, 12(1), 268–276. https://ijritcc.org/index.php/ijritcc/article/view/10252
24. Ntoutsi, E., Fafalios, P., Gadiraju, U., Iosifidis, V., Nejdl, W., Vidal, M. E., ... & Staab, S. (2020). Bias in data-driven artificial intelligence systems—An introductory survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10(3), e1356. https://doi.org/10.1002/widm.1356
25. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, n71. https://doi.org/10.1136/bmj.n71
26. Parasuraman, A. (2000). Technology Readiness Index (TRI): A multiple-item scale to measure readiness to embrace new technologies. Journal of Service Research, 2(4), 307–320. https://doi.org/10.1177/109467050024001

27. Pfeffer, J., & Salancik, G. R. (1978). The external control of organizations: A resource dependence perspective. Harper & Row.
28. Rogers, E. M., Singhal, A., & Quinlan, M. M. (2014). Diffusion of innovations. In An integrated approach to communication theory and research (pp. 432–448). Routledge.
29. Saudi Data and Artificial Intelligence Authority (SDAIA). (2020). National strategy for data and AI. SDAIA.
30. Saudi Data and Artificial Intelligence Authority (SDAIA). (2023). AI ethics principles (Version 1.0). SDAIA.
31. Templier, M., & Paré, G. (2015). A framework for guiding and evaluating literature reviews. Communications of the Association for Information Systems, 37, 6. https://doi.org/10.17705/1CAIS.03706
32. Thomas, J., & Harden, A. (2008). Methods for the thematic synthesis of qualitative research in systematic reviews. BMC Medical Research Methodology, 8, 45. https://doi.org/10.1186/1471-2288-8-45
33. Tornatzky, L. G., & Fleischer, M. (1990). The processes of technological innovation. Lexington Books.
34. Uren, V., & Edwards, J. S. (2023). Technology readiness and the organizational journey towards AI adoption: An empirical study. International Journal of Information Management, 68, 102588. https://doi.org/10.1016/j.ijinfomgt.2022.102588
35. 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
36. Yadav, S. S. K., & Mishra, G. (2024). Robotic process automation applications across industries: An exploration. In Proceedings of the International Conference on Contemporary Computing and Informatics (pp. 26–32). IEEE. https://ieeexplore.ieee.org/document/10828986
37. 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, 39. https://doi.org/10.1186/s41239-019-0171-0
38. Zednik, C. (2021). Solving the black box problem: A normative framework for explainable artificial intelligence. Philosophy & Technology, 34(2), 265–288. https://doi.org/10.1007/s13347-019-00382-7
39. Zhang, Y., Sun, J., Yang, Z., & Wang, Y. (2020). Critical success factors of green innovation: Technology, organization and environment readiness. Journal of Cleaner Production, 264, 121701. https://doi.org/10.1016/j.jclepro.2020.121701.