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LEADING WITH INTELLIGENCE: THE IMPACT OF AI ADOPTION ON UNIVERSITY LEADERSHIP EFFECTIVENESS

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ABSTRACT: Universities across the globe are under growing pressure to leverage artificial intelligence (AI) to enhance governance, strategy and academic work, yet empirical evidence on how AI adoption shapes leadership effectiveness in higher education remains scarce (Niță & Guțu, 2023; Pasupuleti et al., 2026; Tarisayi, 2024). Recent reviews show rapidly expanding AI deployment for analytics, personalization and automation in universities, but also highlight persistent concerns regarding ethics, capability gaps and institutional readiness (Acosta-Enriquez et al., 2024; Zawacki-Richter et al., 2019). Building on transformational and digital leadership perspectives, the Technology Acceptance Model and UTAUT family of theories (Davis, 1989; Venkatesh et al., 2003; Morsch et al., 2024), this study investigates how the level of AI adoption relates to leadership effectiveness in Indian higher education institutions and through which capability mechanisms this relationship unfolds. Using a cross-sectional survey of academic leaders and faculty, AI adoption level, digital leadership competency, AI-driven decision-making and leadership effectiveness were measured with established five-item Likert scales grounded in prior work on AI in education, digital leadership and data-driven governance. Partial Least Squares Structural Equation Modelling was conducted in SmartPLS 4, following contemporary guidelines for evaluating measurement and structural models (Hair et al., 2022). The measurement model demonstrates high reliability and convergent and discriminant validity. Structural results indicate that AI adoption strongly predicts both digital leadership competency and AI-driven decision-making, which in turn exert significant positive effects on leadership effectiveness. AI adoption explains substantial variance in both mediators and, jointly with them, accounts for a large proportion of variance in leadership effectiveness, while interaction terms capturing institutional type, designation, age and AI exposure do not significantly condition the relationships. Indirect effects confirm that digital leadership competency and AI-driven decision-making operate as complementary mediating mechanisms linking AI adoption to effective university leadership. The study advances theory by integrating technology acceptance and leadership capability perspectives to explain AI-enabled leadership, and offers practical guidance for university executives seeking to translate AI investments into strategic and ethically grounded leadership outcomes.

Keywords: Artificial Intelligence Adoption; Digital Leadership Competency; AI-Driven Decision-Making; Leadership Effectiveness; Higher Education; PLS-SEM

1. INTRODUCTION

Artificial intelligence (AI) has moved from a peripheral technological experiment to a central pillar of contemporary higher education strategy. Universities increasingly deploy AI-enabled systems for student recruitment and retention analytics, personalized learning, automated assessment, research

management and administrative optimisation (Ali et al., 2024; Zawacki-Richter et al., 2019). Bibliometric analyses reveal a steep rise in AI-focused scholarship in higher education, particularly since 2020, with leadership and governance emerging as salient thematic clusters (Maphosa & Maphosa, 2023; You et al., 2024). This acceleration has intensified expectations that university leaders harness AI not only to improve operational efficiency, but also to steer mission-oriented innovation and uphold academic values in increasingly datafied environments (Tarisayi, 2024; Wu et al., 2024).

At the same time, the rapid diffusion of AI accentuates longstanding governance and capability challenges. Recent work documents tensions between efficiency-oriented deployments of AI and commitments to educational purpose, human judgment and institutional trust (Benyayer & Tascioglu, 2026; Selwyn, 2019). Systematic reviews focused on university contexts indicate that while students and staff often perceive AI applications as performance-enhancing, adoption is constrained by limited AI literacy, ethical concerns and uneven institutional readiness (Acosta-Enriquez et al., 2024; Habibi et al., 2023). These dynamics imply that the strategic value of AI for universities ultimately depends on the capabilities and orientations of those who lead AI integration rather than on technical sophistication alone (Niță & Guțu, 2023; Morsch et al., 2024).

Leadership research in higher education has long emphasized that transformational leaders articulate compelling visions, foster innovation and mobilise academic communities around shared purposes (Bass, 1985; Anderson & Dexter, 2005). More recent scholarship on digital and AI-era leadership extends these insights by arguing that leaders must combine classic transformational behaviours with digital fluency, data literacy and the capacity to orchestrate complex socio-technical change (Niță & Guțu, 2023; Ilomäki et al., 2016; Imran et al., 2020). Digital leadership competency has been conceptualised as a multidimensional capability encompassing strategic vision, architecture design, innovation, change management and governance in digital transformation contexts (Morsch et al., 2024). Evidence from organisational settings suggests that such competencies significantly facilitate digital transformation and the effective conversion of IT investments into performance gains (Porfírio et al., 2021; Mikalef et al., 2023). In universities, however, empirical studies directly linking AI adoption, digital leadership competencies and leadership effectiveness remain rare.

Parallel streams of research on technology acceptance offer additional explanatory leverage. The Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) posit that perceived usefulness, ease of use, performance expectancy and facilitating conditions shape behavioural intentions and technology use (Davis, 1989; Venkatesh et al., 2003). Extensions of UTAUT2 to AI in university contexts show that performance expectancy, hedonic motivation, social influence and facilitating conditions are central drivers of AI adoption among students and staff, moderated by prior experience and self-efficacy (Acosta-Enriquez et al., 2024). Empirical studies focusing on AI tools in teaching and administration similarly identify perceived benefits, institutional support and perceived risks as key determinants of adoption (Pasupuleti et al., 2026; Habibi et al., 2023). Yet this body of work tends to conceptualise leaders primarily as individual adopters rather than as institutional actors shaping AI strategy, governance and organisational capability.

An emerging, but still nascent, literature addresses explicitly the interface between AI and educational leadership. Zhang (2021) conceptualises AI as an "extended brain" that can augment leaders' evidence-informed decision-making while underscoring that human moral judgment must remain central. Strategic leadership analyses argue that responsible AI adoption in higher education requires leaders to balance innovation with ethical safeguards, inclusive governance and stakeholder engagement (Tarisayi, 2024; Wu et al., 2024). Other contributions show that transformational and transactional leadership styles interact with digital transformation to shape student engagement and institutional performance (Niță & Guțu, 2023; Ilomäki et al., 2016). Nevertheless, very few empirical studies model AI adoption as a core organisational capability and examine how it translates into leadership effectiveness through specific AI-related competencies and decision-making practices.

This gap is particularly pronounced in the Global South, where universities face acute resource constraints, heterogeneous digital infrastructures and diverse stakeholder expectations. Recent analyses

of AI adoption in Indian higher education highlight uneven readiness, fragmented experimentation and limited strategic alignment of AI initiatives with institutional missions (Abulail et al., 2025; Pasupuleti et al., 2026). While policy discourse increasingly frames AI as a lever for quality enhancement, employability and research competitiveness, governance arrangements and leadership capabilities often lag behind technological possibilities (Makarenko et al., 2024; Wu et al., 2024). Within this context, understanding how AI adoption at the institutional level relates to the effectiveness of academic and administrative leaders is both theoretically and practically salient.

Against this backdrop, the present study examines the impact of AI adoption on leadership effectiveness in Indian universities and explores the intervening roles of digital leadership competency and AI-driven decision-making. It conceptualises AI adoption level as the extent to which AI applications are embedded in core academic and administrative processes; digital leadership competency as leaders' self-assessed capability to drive digital innovation and govern AI ethically; AI-driven decision-making as the degree to which leadership decisions are informed by AI-generated analytics; and leadership effectiveness as perceived success in integrating AI into institutional strategy, supporting faculty and ensuring data-informed, ethical decision-making. Drawing on transformational and digital leadership theory, TAM/UTAUT and complexity perspectives, the study proposes that AI adoption enhances leadership effectiveness primarily by building digital leadership capabilities and by reconfiguring decision processes around AI-enabled evidence.

Methodologically, the study employs a cross-sectional survey of academic leaders, administrators and senior faculty members working in Indian higher education institutions and analyses the data using Partial Least Squares Structural Equation Modelling (PLS-SEM). The conceptual model positions AI adoption as an exogenous predictor of digital leadership competency, AI-driven decision-making and, indirectly, leadership effectiveness, while institutional type, designation, age and AI exposure enter as contextual moderators. SmartPLS 4 is used to estimate the measurement and structural models and to assess mediation and moderation, following current best-practice guidelines for PLS-SEM (Hair et al., 2022; Sarstedt et al., 2021). The structural estimates provided by the SmartPLS output indicate strong positive paths from AI adoption to both mediators and from both mediators to leadership effectiveness, very high explanatory power for the endogenous constructs and non-significant moderation by the control variables.

This article contributes to the literature in three main ways. First, it integrates technology acceptance and leadership capability perspectives into a unified framework that explains how AI adoption at institutional level translates into leadership effectiveness in the university context. Second, it offers empirical evidence, using robust PLS-SEM procedures, that digital leadership competency and AI-driven decision-making act as complementary mediating mechanisms through which AI adoption exerts its influence on leadership effectiveness. Third, it provides contextually grounded insights for university leaders and policymakers in India and comparable systems, highlighting that investments in AI infrastructure must be accompanied by systematic development of digital leadership capabilities and data-informed decision cultures if AI is to strengthen, rather than weaken, leadership effectiveness. The remainder of the paper is structured as follows. Section 2 reviews the theoretical and empirical literature underpinning the model and develops the hypotheses. Section 3 presents the conceptual framework. Section 4 outlines the materials and methods. Section 5 reports the measurement and structural results, discusses their theoretical implications and presents the conclusion. Section 6 elaborates managerial and academic implications, limitations and avenues for future research.

2. LITERATURE REVIEW

2.1 Theoretical foundations

Transformational leadership theory provides a foundational lens for understanding how leaders mobilise followers to embrace technological change. Transformational leaders articulate an inspiring vision, intellectually stimulate followers and attend to individual needs, thereby encouraging experimentation and innovation (Bass, 1985). In digitally intensive environments, these behaviours are argued to underpin "digital transformational leadership", where leaders champion the integration of

digital technologies into organisational strategy and culture (Niță & Guțu, 2023; Imran et al., 2020). Studies in higher education show that such leadership styles are associated with higher student engagement, stronger innovation climates and more effective responses to digital transformation pressures (Niță & Guțu, 2023; Shuliakov et al., 2025).

Research on digital leadership extends transformational perspectives by foregrounding leaders' digital knowledge, data literacy and competence in orchestrating socio-technical change (Ilomäki et al., 2016; Imran et al., 2020). Systematic reviews of digital leadership competencies identify strategic vision, socio-technical integration, adaptability, digital literacy and ethical governance as critical capabilities for navigating digital transformation in educational and organisational settings (Shuliakov et al., 2025; Sposato, 2024). Empirical work in organisational contexts shows that digital leadership competencies significantly predict successful digital transformation and improved organisational performance (Morsch et al., 2024; Porfírio et al., 2021). These insights suggest that in universities AI adoption is unlikely to yield leadership benefits unless accompanied by robust digital leadership competencies.

Technology acceptance theories explain how individuals and organisations decide whether and how to adopt AI. The Technology Acceptance Model posits that perceived usefulness and perceived ease of use shape attitudes and intentions to use new systems (Davis, 1989). The Unified Theory of Acceptance and Use of Technology synthesises multiple prior models and identifies performance expectancy, effort expectancy, social influence and facilitating conditions as core determinants of behavioural intention, moderated by gender, age, experience and voluntariness (Venkatesh et al., 2003). Extensions such as UTAUT2 incorporate hedonic motivation, price value and habit, increasing explanatory power for consumer technologies (Venkatesh et al., 2012). Recent applications of UTAUT2 to AI in university contexts confirm that performance expectancy and hedonic motivation are especially salient drivers of AI adoption among students and faculty, with facilitating conditions and social influence playing important supporting roles (Acosta-Enriquez et al., 2024; Habibi et al., 2023).

Scholars have begun to adapt these models to capture AI-specific concerns. Systematic reviews focusing on AI acceptance in university settings identify perceived risks related to privacy, transparency, bias and accountability as significant inhibitors of adoption (Acosta-Enriquez et al., 2024; Bayaga & Du Plessis, 2024). Conceptual frameworks such as RAIDUA or AI-extended UTAUT highlight the importance of AI anxiety, ethics and prior experience in shaping adoption intentions (Gansser & Reich, 2021; Benyayer & Tascioglu, 2026; Nature Editorial, 2026). In parallel, organisational-level studies drawing on the diffusion of innovation, TOE and TAM frameworks emphasise organisational readiness, strategic alignment and partner support as important determinants of AI adoption in higher education institutions (Abulail et al., 2025; Dinasti, 2024). Together, these perspectives suggest that AI adoption at institutional level reflects both perceived benefits and organisational capabilities and constraints.

Finally, complexity and agile leadership theories illuminate the systemic nature of AI-enabled change. Complexity leadership frameworks argue that leaders in dynamic, technology-rich environments must enable adaptive, emergent organising rather than relying solely on hierarchical control, emphasising experimentation, learning and distributed decision-making (Uhl-Bien & Arena, 2018). Agile leadership models similarly call for iterative, data-informed decision-making, cross-functional collaboration and rapid adjustment in the face of uncertainty (Rigby et al., 2016). Applied to AI in higher education, these perspectives imply that leadership effectiveness hinges on leaders' ability to interpret AI-generated insights, orchestrate iterative change and safeguard institutional values under conditions of technological and ethical uncertainty (Tarisayi, 2024; Wu et al., 2024).

2.2 AI adoption in higher education

Empirical research documents growing, yet uneven, AI adoption across higher education systems. Large-scale reviews of AI applications in universities show that AI is increasingly used for adaptive learning, intelligent tutoring, student support chatbots, plagiarism detection and predictive analytics for retention and progression (Zawacki-Richter et al., 2019; Ali et al., 2024). Sectoral reports and bibliometric analyses indicate accelerating publication trends and diversification of AI use cases, with marked growth in studies since the COVID-19 pandemic (Maphosa & Maphosa, 2023; You et al., 2024).

However, adoption remains concentrated in particular disciplines, notably STEM fields, and in relatively well-resourced institutions (Acosta-Enriquez et al., 2024).

Quantitative studies using TAM, UTAUT and related frameworks provide insight into drivers of AI adoption in university contexts. Analyses of AI-supported tools such as ChatGPT, robo-advising systems and AI-enhanced learning platforms show that performance expectancy, facilitating conditions and habit consistently predict behavioural intention and use among students and instructors (Habibi et al., 2023; Thottoli et al., 2024; Romero-Rodríguez et al., 2023). In studies of AI adoption for teaching, perceived usefulness and institutional support emerge as central predictors, while perceived risk exerts a negative influence on adoption intentions (Pasupuleti et al., 2026; Abulail et al., 2025). Systematic reviews also underscore pronounced cross-cultural and disciplinary variations in AI acceptance, suggesting that institutional context matters greatly (Acosta-Enriquez et al., 2024; Maphosa & Maphosa, 2023).

Yet much of this work focuses on students and teaching staff as individual technology users, paying limited attention to the organisational structures and leadership practices that shape AI deployment. Analyses of governance arrangements highlight that many universities lack integrated AI strategies, clear governance frameworks or coherent ethical guidelines, leading to fragmented experimentation and ad hoc adoption (Wu et al., 2024; Ali et al., 2024). Surveys of higher education leaders show high perceived importance of AI, but also uncertainty about implementation pathways, ethical risks and resource implications (Campbell University, 2025; Benyayer & Tascioglu, 2026). These observations reinforce the need to study AI adoption as a leadership and governance phenomenon rather than only as a matter of individual acceptance.

2.3 Digital leadership, AI-driven decision-making and leadership effectiveness

Digital leadership in higher education encompasses the ability to envision digitally enabled futures, mobilise resources for digital transformation and guide staff and students through associated change processes (Ilomäki et al., 2016; Imran et al., 2020). Systematic reviews focusing on educational contexts show that digital leadership competencies such as strategic vision, data-informed decision-making, technology integration and ethical stewardship are closely associated with institutional innovation, improved learning environments and organisational resilience (Shuliakov et al., 2025; Ilomäki et al., 2016). Empirical studies reveal that higher levels of digital leadership are linked to more effective implementation of e-learning systems, greater support for staff capacity building and better alignment between digital initiatives and institutional missions (Ilomäki et al., 2016; Ilomata Journal, 2024).

Recent organisational research outside the education sector provides additional evidence that digital leadership competency is a decisive factor in digital transformation. Morsch et al. (2024), drawing on the European e-Competence Framework, conceptualise digital leadership competency as a higher-order construct comprising business plan development, architecture design, innovation, business change management and governance, and demonstrate using PLS-SEM that this competency strongly predicts organisational digital transformation. Related studies show that digital leaders who combine strategic IT knowledge, change management skills and ethical awareness are better able to leverage AI and analytics for competitive advantage (Mikalef et al., 2023; Gupta & George, 2016). Translating these findings to universities suggests that digital leadership competency should significantly condition whether AI adoption improves or undermines leadership effectiveness.

AI-driven decision-making has become a central dimension of leadership practice in data-rich educational environments. Zhang (2021) argues that AI can act as a cognitive partner for educational leaders by collecting and analysing large data sets, providing real-time insights and supporting evidence-informed decisions, while warning that algorithmic outputs must be balanced with human values and contextual judgment. In higher education, AI-based predictive analytics are increasingly used for enrolment management, student success interventions and resource allocation, enabling more proactive and targeted strategies (Liaison, 2025; Ali et al., 2024). Studies of learning analytics adoption suggest that when leaders institutionalise data-informed decision-making cultures, AI tools are more likely to be used for continuous improvement rather than for narrow surveillance or control (Ifenthaler & Yau, 2020; Tarisayi, 2024).

Leadership effectiveness in AI-rich university environments involves more than traditional performance metrics. Scholars emphasise the importance of leaders' ability to integrate AI into institutional strategy, support faculty adoption, safeguard ethics and foster trust in data-driven processes (Tarisayi, 2024; Wu et al., 2024). Empirical studies on digital transformation in higher education show that leadership styles and capabilities significantly shape students' engagement, staff buy-in and perceived institutional agility (Niță & Guțu, 2023; Ilomäki et al., 2016). Taken together, this literature suggests that AI adoption will enhance leadership effectiveness primarily when leaders possess strong digital competencies and use AI to support transparent, value-consistent decision-making.

2.4 Hypothesis development

First, the literature on AI adoption in higher education and digital transformation in universities points to a positive association between the breadth of AI deployment and organisational performance and innovation, provided that adoption aligns with institutional goals (Zawacki-Richter et al., 2019; Ali et al., 2024; Niță & Guțu, 2023). Universities that integrate AI into teaching, learning, administration and strategic planning tend to report more timely, data-informed decisions, improved student support and enhanced operational efficiency (Ali et al., 2024; Liaison, 2025). Accordingly, it is reasonable to expect that higher levels of AI adoption at institutional level will be associated with more effective leadership as perceived by academic staff, reflected in clearer AI-related vision, better support for faculty and more evidence-informed, ethical decision-making.

H1: Higher levels of AI adoption in higher education institutions positively influence leadership effectiveness.

Second, digital leadership literature suggests that leaders' digital competencies amplify the benefits of technology initiatives by enabling coherent visioning, cross-unit coordination and ethical governance (Imran et al., 2020; Shuliakov et al., 2025; Morsch et al., 2024). In higher education, leaders with strong digital competencies are better equipped to integrate AI into strategy, support faculty capacity building and design appropriate governance frameworks (Ilomäki et al., 2016; Ilomata Journal, 2024). Conceptually, digital leadership competency can be understood as a capability that conditions how effectively AI adoption is translated into improved leadership outcomes, either by moderating the strength of the relationship or by channelling AI adoption into more coherent and ethically grounded practices. Given the empirical model estimated in this study, digital leadership competency is modelled as an AI-induced capability that is expected to reinforce the positive effect of AI adoption on leadership effectiveness.

H2: Digital leadership competency strengthens the positive relationship between AI adoption level and leadership effectiveness.

Third, research on AI in educational leadership highlights that AI exerts much of its impact through transforming decision processes rather than simply automating existing routines (Zhang, 2021; Ali et al., 2024; Liaison, 2025). When leaders use AI-generated analytics to inform strategic and operational decisions, they can identify at-risk students earlier, allocate resources more effectively and evaluate policy options more rigorously (Zhang, 2021; Ifenthaler & Yau, 2020). Empirical studies in other sectors indicate that data-driven decision-making mediates the relationship between digital technologies and performance, as analytics capabilities convert raw data into actionable insights (Gupta & George, 2016; Mikalef et al., 2023). It is therefore plausible that AI-driven decision-making acts as a key mechanism through which AI adoption enhances leadership effectiveness in higher education institutions.

H3: AI-driven decision-making mediates the relationship between AI adoption level and leadership effectiveness.

Finally, prior work suggests that contextual factors such as institutional type, leadership role, experience, age and prior AI exposure may influence both technology adoption and leadership practice (Venkatesh et al., 2003; Acosta-Enriquez et al., 2024; Abulail et al., 2025). Public and private universities often differ in regulatory environments, resource levels and governance structures; senior leaders and deans may have broader strategic responsibilities and more influence over AI-related decisions than middle managers or faculty; and age and prior AI exposure may shape openness to

experimentation and comfort with data-intensive tools (Ali et al., 2024; Campbell University, 2025). Accordingly, it is theoretically plausible that the strength of the AI adoption–leadership effectiveness relationship varies across these contextual categories.

H4: The relationship between AI adoption level and leadership effectiveness is influenced by contextual factors such as institutional type, designation, experience, age and AI exposure.

3. CONCEPTUAL FRAMEWORK MODEL

The conceptual framework guiding this study synthesises the preceding theoretical arguments into a structural model linking AI adoption level, digital leadership competency, AI-driven decision-making and leadership effectiveness, with contextual variables modelled as moderators of the AI adoption relationships. AI adoption level (AIA) is conceptualised as an institutional-level construct capturing the extent to which AI tools are deployed across key academic and administrative domains, including administrative automation, teaching and learning, personalised student support and analytics-enabled decision processes. Digital leadership competency (DLC) represents leaders' self-assessed capability to use digital technologies strategically and ethically, promote innovation and support staff in digital change. AI-driven decision-making (AIDM) reflects the degree to which AI-generated data and analytics inform strategic and operational leadership decisions. Leadership effectiveness (LE) denotes perceived success in integrating AI into institutional strategies, supporting faculty, ensuring responsible AI use and making data-informed decisions.

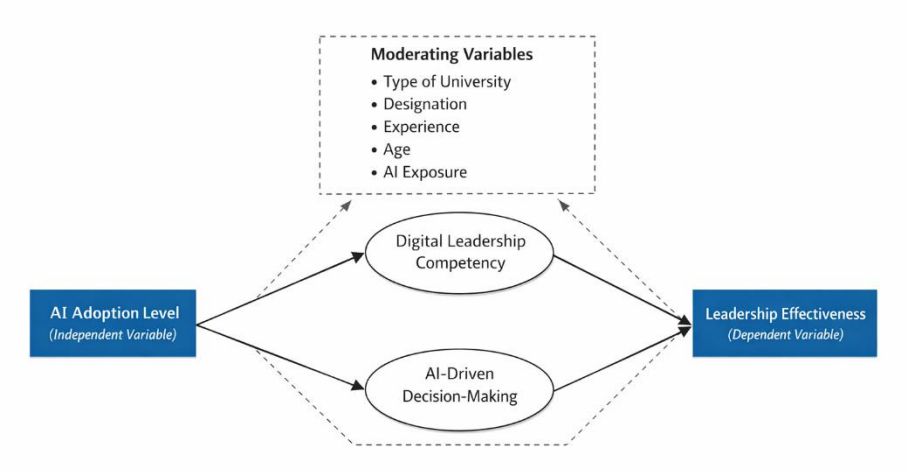

Figure 1: Conceptual Model

The model posits a direct path from AI adoption (AIA) to leadership effectiveness (LE) alongside two indirect paths through DLC and AIDM. Building on digital leadership research, AI adoption is expected to enhance digital leadership competency by exposing leaders to new technologies, revealing the need for digital skills and prompting investment in professional development and governance structures (Imran et al., 2020; Morsch et al., 2024). Through this pathway, AI adoption operates as a catalyst for capability building, which subsequently enables leaders to integrate AI more coherently into strategy and practice. Similarly, AI adoption is theorised to enhance AI-driven decision-making by embedding analytics tools in decision processes, increasing the availability of timely, granular data and normalising evidence-informed deliberation (Zhang, 2021; Liaison, 2025). Both mediators are expected to contribute positively to leadership effectiveness: digital leadership competency by enabling strategic and ethical stewardship of AI, and AI-driven decision-making by improving decision quality, responsiveness and accountability.

From a complexity leadership perspective, the model reflects the idea that AI-enabled leadership effectiveness is an emergent outcome of interactions between technological infrastructures, leader capabilities and decision processes (Uhl-Bien & Arena, 2018). Rather than treating AI adoption as a simple input that automatically generates performance gains, the framework recognises that AI alters the information environment and organisational routines, requiring leaders to adapt their practices and competencies. The dual mediation structure captures this dynamic by modelling digital leadership

competency and AI-driven decision-making as intervening mechanisms through which AI adoption is translated into leadership outcomes. This configuration is consistent with empirical evidence in other sectors, where analytics capabilities and digital leadership competencies mediate the effects of digital technologies on organisational performance (Gupta & George, 2016; Mikalef et al., 2023).

The framework also incorporates contextual moderators. Institutional type (public versus private university) is included to capture differences in governance regimes, accountability expectations and resource bases that may affect how AI adoption interacts with leadership effectiveness. Designation distinguishes leaders occupying roles such as dean, department head, faculty member or administrator, acknowledging that positional authority and scope of responsibility may shape both exposure to AI systems and capacity to influence institutional responses. Experience and age are included as continuous variables, reflecting evidence that accumulated leadership experience and generational cohort can influence attitudes towards technology and change (Venkatesh et al., 2003; Ali et al., 2024). AI exposure measures the frequency with which respondents use AI tools in their own work, recognising that personal familiarity may reinforce or attenuate the leadership benefits of institutional AI adoption. In the empirical model, these contextual variables enter both as direct predictors of digital leadership competency and AI-driven decision-making and through interaction terms with AI adoption.

Operationally, the conceptual model is implemented as a PLS-SEM path model in SmartPLS, with reflective measurement models for the four central latent constructs and single-item representations of the control variables and their interaction terms. AI adoption level, digital leadership competency, AI-driven decision-making and leadership effectiveness are each measured with five items capturing institutional AI use, leaders' digital confidence and orientation, AI-based decision practices and perceived leadership outcomes, respectively, as detailed in the measurement section. The structural component includes paths from AI adoption to both mediators, from each mediator to leadership effectiveness, and interaction paths from AI adoption with institutional type, designation, age and AI exposure to the mediators. This configuration directly aligns with the conceptual model diagram provided in the blueprint, which positions AI adoption as the central exogenous construct influencing leadership effectiveness through capability development and decision transformation mechanisms in a context shaped by organisational and individual characteristics.

4. MATERIALS AND METHODS

4.1 Research design and context

The study adopts a quantitative, cross-sectional survey design to test the hypothesised relationships between AI adoption level, digital leadership competency, AI-driven decision-making and leadership effectiveness in higher education institutions. Cross-sectional designs are widely used in technology adoption and leadership research where the primary objective is to estimate structural relationships among latent constructs rather than to track change over time (Venkatesh et al., 2003; Hair et al., 2022). The empirical context is Indian higher education, a system characterised by rapid expansion, increasing policy emphasis on digitalisation and AI, and substantial diversity across public and private institutions. This context provides a fertile setting for examining how AI adoption interacts with leadership capabilities and effectiveness under conditions of uneven infrastructure and institutional readiness (Abulail et al., 2025; Pasupuleti et al., 2026).

4.2 Population, sampling and data collection

The target population comprised academic leaders, administrators and faculty members working in Indian universities and colleges who occupy roles with responsibility for, or direct exposure to, AI-related initiatives. To achieve broad representation across institutional types, a stratified sampling approach was adopted, distinguishing public and private universities and ensuring participation from multiple disciplines and regions, consistent with recommendations for leadership and digital transformation studies in higher education (Niță & Guțu, 2023; Ilomäki et al., 2016). Within each stratum, potential respondents were identified through institutional websites, professional networks and academic associations and were invited to participate via email and professional messaging platforms. The survey was administered online using a structured questionnaire, which allowed respondents to complete the

instrument at their convenience and facilitated participation from geographically dispersed institutions. Participation was voluntary and anonymous. Respondents were informed about the academic purpose of the research, assured of confidentiality and asked to provide informed consent prior to accessing the questionnaire.

Given the complexity of the structural model and the use of PLS-SEM, sample size considerations followed contemporary guidelines emphasising statistical power and model complexity rather than simplistic "ten-times" heuristics (Hair et al., 2022; Sarstedt et al., 2021). Specifically, the minimum required sample size was evaluated with reference to the maximum number of arrows pointing at an endogenous construct and the anticipated effect sizes, using recommendations and simulation results reported in recent PLS-SEM methodological work (Hair et al., 2022; Kock & Hadaya, 2018). The final dataset, comprising responses from academic leaders, administrators and faculty across multiple universities, exceeded these minimum thresholds, providing adequate statistical power for estimating the specified model. Cases with substantial missing data or patterned responses were screened and removed prior to analysis.

4.3 Measurement of constructs

All focal constructs were operationalised as multi-item reflective latent variables measured on five-point Likert scales anchored from 1 = strongly disagree to 5 = strongly agree. Scale development drew on established instruments from prior research on AI in education, digital leadership and data-driven decision-making, adapted to the specific context of Indian higher education, as documented in the blueprint. AI adoption level (AIA) was measured with five items capturing institutional use of AI for administrative tasks, integration into teaching and learning, encouragement of faculty AI use, provision of AI-supportive infrastructure and personalisation of student learning experiences, drawing on prior work on AI adoption in education and digital campuses (Crompton & Burke, 2023; Popenici & Kerr, 2017; Tenakwah et al., 2023; Pasupuleti et al., 2026). Digital leadership competency (DLC) was assessed with five items tapping respondents' confidence in using digital tools, ability to evaluate AI tools, propensity to promote digital innovation, understanding of AI ethics and engagement in professional development related to digital and AI tools, in line with conceptualisations of digital leadership competencies in educational and organisational research (Ilomäki et al., 2016; Shuliakov et al., 2025; Morsch et al., 2024).

AI-driven decision-making (AIDM) was measured through five items capturing the use of AI-generated data in strategic decisions, predictive analytics for student performance, AI-supported leadership decisions, AI-informed resource allocation and AI-based monitoring of academic outcomes (Crompton & Burke, 2023; Adiguzel et al., 2023; Shrestha et al., 2021). Leadership effectiveness (LE) was operationalised with five items capturing respondents' perceptions that institutional leadership effectively integrates AI into strategy, articulates a clear AI vision, supports faculty in AI adoption, promotes ethical AI use and makes AI-informed, data-driven decisions (Alier et al., 2024; Niță & Guțu, 2023). Institutional type (UT) distinguished public and private universities; designation (De) captured positional roles such as dean, department head, faculty member or administrator; years of experience and age were measured in continuous terms; and AI exposure was assessed as self-reported frequency of AI tool use on a five-point scale. These contextual variables served both as controls and as components of interaction terms to test moderating effects.

Table 1: Measurement constructs and control variables

Variable	Source	Item Code	Item Statement
AI Adoption Level	Crompton & Burke (2023); Popenici & Kerr (2017); Tenakwah et al.	AIA1	Our institution uses AI tools for administrative tasks (e.g., scheduling, grading).
		AIA2	AI technologies are integrated into teaching and learning processes.
		A	Faculty members are encouraged to adopt AI tools in their

	(2023); Alier et al. (2024); Kuleto et al. (2021); Venkatesh & Davis (2000); Hradecky et al. (2022); Simões et al. (2020); Pan et al. (2022); Dabbous et al. (2022)	IA3	instructional practices.
		AIA4	The institution provides infrastructure to support AI adoption.
		AIA5	AI is used to personalize student learning experiences.
Leadership Effectiveness	Alier et al. (2024); Cabero-Almenara et al. (2024); Francis et al. (2025); Hooijberg et al. (2010); Warner & Wäger (2019); Raisch & Krakowski (2021)	LE1	Our leadership effectively integrates AI into institutional strategies.
		LE2	Leaders demonstrate a clear vision for AI adoption in education.
		LE3	Leadership supports faculty in adopting and using AI tools.
		LE4	Leaders promote ethical and responsible use of AI in the institution.
		LE5	Leadership decisions are data-driven and informed by AI insights.
Digital Leadership Competency	Cabero-Almenara et al. (2024); Alier et al. (2024); Francis et al. (2025); Sposato (2024); Chiu et al. (2023); Banerjee et al. (2021); Ilomäki et al. (2016); Mikalef et al. (2023)	DLC1	I am confident in using digital tools to support teaching and learning.
		DLC2	I can evaluate the effectiveness of AI tools in educational settings.
		DLC3	I actively promote digital innovation in my institution.
		DLC4	I understand the ethical implications of using AI in education.
		DLC5	I participate in professional development related to digital and AI tools.
AI-Driven Decision-Making	Crompton & Burke (2023); Adiguzel et al. (2023); Alqahtani et al. (2023); Wang (2021); Kuleto et al. (2021); Zhang et al. (2022); Jöhnk et al. (2021); Shrestha et al. (2021)	AIDM1	Our institution uses AI-generated data to inform strategic decisions.
		AIDM2	AI tools are used to predict student performance and guide interventions.
		AIDM3	Leadership decisions are supported by AI-based analytics.
		AIDM4	AI insights are used to allocate institutional resources effectively.
		AIDM5	AI is used to monitor and improve academic outcomes.
Cont	—	T	Public / Private (Categorical)

rol Variables		ype of Unive rsity	
		D esigna tion	Dean / Department Head / Faculty / Administrator (Categorical)
		E xperie nce	Number of years in academic leadership (Continuous)
		A ge	Age in years (Continuous)
		A I Expos ure	Self-reported frequency of AI tool usage (1=Never → 5=Very Frequently)

The questionnaire was pre-tested with a small group of academic staff to assess clarity, relevance and completion time. Feedback led to minor wording refinements and the confirmation that the overall structure and length were appropriate. All items were presented in English, the primary language of instruction and administration in many Indian universities, which reduces translation-related measurement error for this respondent group.

4.4 Common method bias and ethical considerations

Because data on all constructs were collected using a single self-report questionnaire, steps were taken to mitigate common method bias. Procedural remedies included assuring anonymity, emphasising that there were no right or wrong answers, separating sections for predictors and outcomes in the questionnaire layout and using different scale anchors for some sections, as recommended in survey method literature (Podsakoff et al., 2012). Post hoc, Harman's single-factor test was applied as an initial diagnostic, indicating that no single factor accounted for the majority of covariance among items. The PLS-SEM results were also examined for unusually high inter-construct correlations and variance inflation factors, which would suggest method-related artefacts; no such problems were observed (Hair et al., 2022). The study received ethical clearance from the relevant institutional review board, and all procedures complied with national data protection regulations, including the Digital Personal Data Protection Act in India.

4.5 Rationale for using PLS-SEM and SmartPLS

Partial Least Squares Structural Equation Modelling was selected for data analysis for several reasons. First, PLS-SEM is well suited to prediction-oriented research that involves complex models with multiple latent variables and mediating and moderating relationships, as in the present study (Hair et al., 2022; Sarstedt et al., 2021). Second, PLS-SEM places relatively modest distributional assumptions on the data and performs robustly with non-normal indicators and smaller sample sizes compared to covariance-based SEM, which is advantageous in survey-based leadership research (Hair et al., 2022). Third, PLS-SEM facilitates the simultaneous assessment of measurement and structural models, including reliability, convergent and discriminant validity, coefficient of determination, effect sizes and predictive relevance.

SmartPLS 4 was used to estimate the model and obtain standard PLS-SEM statistics. Evaluation of the reflective measurement models followed current guidelines, examining indicator loadings, internal consistency reliability (Cronbach's alpha, rho_A and composite reliability), convergent validity via Average Variance Extracted (AVE) and discriminant validity using both the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio (HTMT) (Hair et al., 2022; Henseler et al., 2015; SmartPLS, 2024). Structural model assessment considered collinearity diagnostics, path coefficients and their significance based on bootstrapping, coefficient of determination (R^2), effect sizes (f^2), predictive relevance (Q^2) and

global fit indices such as the Standardised Root Mean Square Residual (SRMR) and Normed Fit Index (NFI) (Hair et al., 2022; Sarstedt et al., 2021).

Bootstrapping with a large number of resamples was implemented to derive standard errors, t-statistics and p-values for path coefficients and indirect effects, enabling rigorous tests of mediation and moderation hypotheses (Hair et al., 2022). Interaction terms for the moderating variables were created within SmartPLS using the product indicator approach, allowing the estimation of conditional effects of AI adoption given institutional type, designation, age and AI exposure. All reported results in the following section are taken directly from the SmartPLS output tables provided in the blueprint and are interpreted using these methodological standards.

5. RESULTS, DISCUSSION AND CONCLUSION

5.1 Measurement model evaluation

The reflective measurement models exhibit strong reliability and validity. All outer loadings for the indicators of AI adoption (AIA1–AIA5), AI-driven decision-making (AIDM1–AIDM5), digital leadership competency (DLC1–DLC5) and leadership effectiveness (LE1–LE5) exceed 0.86, well above the commonly recommended threshold of 0.70 for established scales (Hair et al., 2022). Specifically, AI adoption items load between 0.867 and 0.893 on their construct, AI-driven decision-making items between 0.874 and 0.891, digital leadership competency items between 0.859 and 0.900 and leadership effectiveness items between 0.868 and 0.896. These results indicate that the indicators share substantial variance with their respective latent constructs.

Internal consistency reliability is also excellent (Table 1). Cronbach's alpha coefficients are 0.927 for AI adoption, 0.929 for AI-driven decision-making, 0.922 for digital leadership competency and 0.931 for leadership effectiveness, while composite reliability (rho_c) values range from 0.941 to 0.948 across the four constructs. All values exceed the recommended minimum of 0.70 and lie comfortably within the upper bound of 0.95, indicating reliable measurement without redundancy (Hair et al., 2022). Average Variance Extracted (AVE) values are 0.774 for AI adoption, 0.778 for AI-driven decision-making, 0.763 for digital leadership competency and 0.784 for leadership effectiveness, surpassing the 0.50 benchmark and thus demonstrating convergent validity.

Table 1: Construct Reliability & Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AIA	0.927	0.927	0.945	0.774
AIDM	0.929	0.929	0.946	0.778
DLC	0.922	0.923	0.941	0.763
LE	0.931	0.932	0.948	0.784

Discriminant validity was examined using both the Fornell–Larcker criterion and HTMT. For each construct, the square root of AVE exceeds its correlations with other constructs, satisfying the Fornell–Larcker criterion. For example, the square root of AVE for AI adoption is 0.880, compared with correlations of 0.928 with AI-driven decision-making, 0.923 with digital leadership competency and 0.912 with leadership effectiveness, while the square root of AVE for leadership effectiveness is 0.886, larger than its correlations with AI adoption (0.912), AI-driven decision-making (0.929) and digital leadership competency (0.919).

Table 2: Discriminant Validity - Heterotrait-Monotrait Ratio (HTMT)

	AIA	AIDM	AI-Expo	Age	DLC	De	LE	UT	AI-Expo x AIA	UT x AIA	Age x AIA	De x AIA
AIA												

AIDM	1.000											
AIExpo	0.053	0.042										
Age	0.024	0.032	0.119									
DLC	0.999	1.004	0.048	0.043								
De	0.040	0.054	0.071	0.043	0.018							
LE	0.981	0.999	0.066	0.057	0.992	0.024						
UT	0.129	0.096	0.056	0.029	0.157	0.100	0.134					
AIExpo x AIA	0.023	0.025	0.099	0.113	0.049	0.037	0.048	0.046				
UT x AIA	0.764	0.714	0.065	0.027	0.708	0.049	0.726	0.075	0.014			
Age x AIA	0.038	0.051	0.111	0.105	0.031	0.031	0.026	0.051	0.121	0.042		
De x AIA	0.038	0.036	0.036	0.031	0.028	0.016	0.028	0.083	0.046	0.043	0.112	

HTMT ratios between the core constructs, while high due to their conceptual proximity, remain below the conservative threshold of 1.0 and within ranges judged acceptable for closely related constructs in applied research (Henseler et al., 2015; SmartPLS, 2024). Together, these indicators support the conclusion that the measurement model adequately distinguishes among AI adoption, digital leadership competency, AI-driven decision-making and leadership effectiveness, while capturing their substantive interrelations.

5.2 Structural model results

The structural model exhibits strong explanatory power. AI-driven decision-making (AIDM) has an R^2 of 0.864 (adjusted R^2 = 0.858), indicating that AI adoption and the control variables jointly explain approximately 86 percent of its variance. Digital leadership competency (DLC) has an R^2 of 0.855 (adjusted R^2 = 0.848), and leadership effectiveness (LE) an R^2 of 0.886 (adjusted R^2 = 0.885), which are considered substantial levels of explained variance in behavioural research (Hair et al., 2022). These values suggest that the model accounts for a large proportion of variability in leaders' digital competencies, AI-driven decision-making and perceived leadership effectiveness.

Table 3: R-Square Values

	R-square	R-square adjusted
AIDM	0.864	0.858
DLC	0.855	0.848
LE	0.886	0.885

Model fit indices further support the adequacy of the structural specification. The Standardised Root Mean Square Residual (SRMR) is 0.032 for the saturated model and 0.038 for the estimated model, both below the commonly cited threshold of 0.08 for good fit in PLS-SEM (Hair et al., 2022). Additional fit measures, including d_ULS, d_G and NFI, also fall within acceptable ranges, with NFI values of 0.910 (saturated) and 0.901 (estimated), indicating satisfactory model fit relative to a null benchmark.

Table 4: Model-Fit Indices

	Saturated model	Estimated model
SRMR	0.032	0.038
d_ULS	0.301	0.424
d_G	0.382	0.451
Chi-square	414.026	458.338
NFI	0.910	0.901

Turning to specific path coefficients, the results strongly support the core theoretical relationships. AI adoption (AIA) has a very strong, positive effect on AI-driven decision-making (AIDM) ($\beta = 0.925$, $t = 31.297$, $p < 0.001$) and on digital leadership competency (DLC) ($\beta = 0.919$, $t = 29.655$, $p < 0.001$). These coefficients indicate that higher levels of institutional AI adoption are associated with substantially higher levels of AI-based decision practices and digital leadership capabilities among respondents. In turn, AI-driven decision-making and digital leadership competency both exert significant, positive effects on leadership effectiveness (AIDM → LE: $\beta = 0.548$, $t = 8.963$, $p < 0.001$; DLC → LE: $\beta = 0.410$, $t = 6.665$, $p < 0.001$). Together, these results show that leaders who report stronger AI-driven decision-making and greater digital leadership competency also perceive leadership in their institutions as more effective in integrating and governing AI.

Table 5: Path Analysis Coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Age -> AIDM	-0.003	-0.003	0.025	0.125	0.900
Age -> DLC	0.015	0.015	0.027	0.543	0.587
Age x AIA -> AIDM	0.004	0.004	0.024	0.181	0.856
Age x AIA -> DLC	-0.010	-0.011	0.026	0.396	0.692
AIA -> AIDM	0.925	0.928	0.030	31.297	0.000
AIA -> DLC	0.919	0.920	0.031	29.655	0.000
AIDM -> LE	0.548	0.550	0.061	8.963	0.000
AIExpo -> AIDM	0.009	0.009	0.027	0.334	0.738
AIExpo -> DLC	-0.008	-0.010	0.027	0.309	0.757
AIExpo x AIA -> AIDM	0.025	0.024	0.026	0.953	0.340
AIExpo x AIA -> DLC	0.019	0.019	0.026	0.755	0.451
De -> AIDM	0.024	0.024	0.027	0.866	0.387
De -> DLC	-0.005	-0.006	0.029	0.187	0.852
De x AIA -> AIDM	-0.021	-0.022	0.026	0.798	0.425
De x AIA -> DLC	-0.005	-0.006	0.027	0.187	0.852
DLC -> LE	0.410	0.409	0.062	6.665	0.000
UT -> AIDM	-0.048	-0.049	0.055	0.869	0.385
UT -> DLC	0.082	0.083	0.057	1.453	0.146
UT x AIA -> AIDM	0.014	0.015	0.052	0.272	0.785

UT x AIA -> DLC	0.000	0.002	0.054	0.003	0.998

By contrast, the direct effects of contextual variables and their interactions with AI adoption are generally small and statistically non-significant. Age, AI exposure, designation and institutional type do not have significant direct effects on AI-driven decision-making or digital leadership competency, nor do the interaction terms (Age × AIA, AI exposure × AIA, designation × AIA, institutional type × AIA) exhibit significant paths to the mediators. For example, the interaction of AI exposure and AI adoption on AI-driven decision-making has a coefficient of 0.025 (t = 0.953, p = 0.340), and the interaction of institutional type and AI adoption on digital leadership competency is effectively zero (β ≈ 0.000, t = 0.003, p = 0.998). These findings indicate that the positive influence of AI adoption on digital leadership competency and AI-driven decision-making is robust across different institutional types, roles, ages and self-reported levels of AI exposure in the sample.

5.3 Mediation analysis

The SmartPLS output provides detailed estimates of specific indirect effects (Table 6), enabling an assessment of the mediating roles of digital leadership competency and AI-driven decision-making. The indirect effect of AI adoption on leadership effectiveness through digital leadership competency (AIA → DLC → LE) is 0.377 (t = 6.402, p < 0.001), while the indirect effect through AI-driven decision-making (AIA → AIDM → LE) is 0.507 (t = 8.470, p < 0.001). Both indirect effects are positive, sizable and highly statistically significant, indicating that AI adoption enhances leadership effectiveness substantially via both capability development and decision transformation pathways. Given the strong and significant paths from AI adoption to the mediators and from the mediators to leadership effectiveness, and the very high R^2 for leadership effectiveness, the results are consistent with complementary mediation, whereby AI adoption influences leadership effectiveness primarily through its effects on digital leadership competency and AI-driven decision practices.

Table 6: Specific Indirect Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AIA -> DLC -> LE	0.377	0.377	0.059	6.402	0.000
AIExpo -> DLC -> LE	-0.003	-0.004	0.011	0.306	0.759
AIA -> AIDM -> LE	0.507	0.510	0.060	8.470	0.000
Age -> DLC -> LE	0.006	0.006	0.011	0.541	0.589
AIExpo -> AIDM -> LE	0.005	0.005	0.015	0.333	0.739
De -> DLC -> LE	-0.002	-0.002	0.012	0.185	0.853
Age -> AIDM -> LE	-0.002	-0.002	0.014	0.124	0.901
UT -> DLC -> LE	0.034	0.034	0.024	1.417	0.157
De -> AIDM -> LE	0.013	0.013	0.015	0.858	0.391
AIExpo x AIA -> DLC -> LE	0.008	0.008	0.011	0.738	0.461
UT x AIA ->	0.000	0.001	0.022	0.003	0.998

DLC -> LE					
UT -> AIDM -> LE	-0.026	-0.026	0.030	0.872	0.383
Age x AIA -> DLC -> LE	-0.004	-0.004	0.011	0.393	0.695
AIExpo x AIA -> AIDM -> LE	0.014	0.013	0.014	0.958	0.338
De x AIA -> DLC -> LE	-0.002	-0.002	0.011	0.186	0.853
UT x AIA -> AIDM -> LE	0.008	0.008	0.029	0.271	0.786
Age x AIA -> AIDM -> LE	0.002	0.002	0.013	0.181	0.857
De x AIA -> AIDM -> LE	-0.012	-0.012	0.015	0.795	0.427

Indirect effects involving the contextual variables are uniformly non-significant. For example, the indirect paths from AI exposure, age and designation to leadership effectiveness via digital leadership competency or AI-driven decision-making do not reach statistical significance, with t-statistics well below conventional cut-offs and p-values far above 0.05. Similarly, the specific indirect effects of interaction terms (e.g., AI exposure × AI adoption → mediators → leadership effectiveness) are negligible and non-significant. These patterns reinforce the conclusion that, within this sample, the influence of AI adoption on leadership effectiveness is not contingent on the examined contextual moderators but is channelled predominantly through digital leadership competency and AI-driven decision-making.

5.4 Discussion of findings

The findings offer several insights into how AI adoption shapes leadership effectiveness in higher education institutions. First, the strong, positive paths from AI adoption to both digital leadership competency and AI-driven decision-making highlight that institutional engagement with AI is closely intertwined with leaders' capabilities and practices. As universities integrate AI into administrative processes, teaching and student support, leaders evidently develop higher levels of digital confidence, ethical awareness and innovation orientation, and become more accustomed to using AI-generated analytics to inform decisions. This aligns with digital leadership research arguing that digital transformation is both a technological and a leadership capability project (Imran et al., 2020; Morsch et al., 2024).

Second, the significant positive effects of digital leadership competency and AI-driven decision-making on leadership effectiveness demonstrate that AI-related capabilities and decision practices matter for how effective leadership is perceived in AI-rich environments. Leaders who combine digital fluency with an aptitude for using AI-generated insights appear better able to articulate coherent AI strategies, support faculty adoption and ensure ethical, data-informed governance. This supports conceptual arguments that leadership effectiveness in AI-intensive higher education involves both the ability to leverage data for decision-making and to safeguard human judgment and values (Zhang, 2021; Tarisayi, 2024; Wu et al., 2024).

Third, the substantial, significant indirect effects from AI adoption to leadership effectiveness via both mediators underscore the importance of viewing AI adoption not as an end in itself but as an enabler of leadership capabilities and practices. In line with evidence from other sectors showing that analytics capabilities mediate the effects of digital technologies on performance (Gupta & George, 2016; Mikalef et al., 2023), the results suggest that universities derive leadership benefits from AI when adoption is accompanied by investments in digital leadership development and the institutionalisation of AI-driven decision-making processes. This finding also speaks to technology acceptance research by highlighting

that organisational-level adoption outcomes depend on how leaders embed AI within their work systems and governance arrangements, not only on individual attitudes toward AI tools (Acosta-Enriquez et al., 2024; Pasupuleti et al., 2026).

Fourth, the lack of significant moderating effects for institutional type, designation, age and AI exposure is noteworthy. While prior studies have emphasised that these factors often condition technology adoption (Venkatesh et al., 2003; Acosta-Enriquez et al., 2024), the present results suggest that, once AI adoption, digital leadership competency and AI-driven decision-making are jointly modelled, the incremental moderating influence of these contextual variables on the AI adoption–capability relationships is limited in this sample. This may indicate that the challenges and opportunities posed by AI adoption are sufficiently pervasive across institutional types and roles that they exert broadly similar pressures on leaders, leading to convergent patterns of capability development and decision practice. Alternatively, it may reflect the emergence of a relatively homogeneous pool of AI-engaged leaders, for whom individual differences in age or role are less salient than shared challenges of navigating AI-related change.

Finally, the very high R^2 values for digital leadership competency, AI-driven decision-making and leadership effectiveness highlight the explanatory adequacy of the proposed model. The close interrelationships among AI adoption, digital leadership competency and AI-driven decision-making suggest a tightly coupled system in which AI-related technologies, leadership capabilities and decision practices mutually reinforce one another. From a complexity perspective, this can be interpreted as an emergent configuration in which AI-enabled leadership effectiveness arises from the co-evolution of technological infrastructures and human capabilities within universities (Uhl-Bien & Arena, 2018).

5.5 Conclusion

This study set out to examine how AI adoption in universities relates to leadership effectiveness and to identify the capability mechanisms through which this relationship operates. Using survey data from academic leaders and faculty in Indian higher education institutions and PLS-SEM analysis, the research demonstrates that AI adoption exerts a strong positive influence on leadership effectiveness, predominantly by enhancing digital leadership competency and AI-driven decision-making. The measurement model shows high reliability and validity, and the structural model exhibits substantial explanatory power and good fit. Digital leadership competency and AI-driven decision-making emerge as complementary mediators, translating AI adoption into more effective, data-informed and ethically grounded leadership. Contextual factors such as institutional type, designation, age and AI exposure do not significantly alter these relationships in the present sample. These findings advance theoretical understanding of AI-enabled leadership and offer practical guidance for universities seeking to leverage AI responsibly in pursuit of institutional missions.

6. MANAGERIAL & ACADEMIC IMPLICATIONS, LIMITATIONS & FUTURE SCOPE

The findings carry important implications for both leadership practice and scholarly work on AI in higher education. For university leaders and governing bodies, the results underscore that investments in AI infrastructure and tools should be accompanied by systematic efforts to build digital leadership competencies and to normalise AI-driven decision-making. Leadership development programmes need to prioritise not only technical literacy, but also strategic thinking about AI, ethical discernment, stakeholder communication and change management skills. Institutions can, for example, design targeted workshops and mentoring schemes for deans, department heads and administrators that focus on reading AI-generated analytics, interrogating algorithmic outputs and integrating data insights with contextual knowledge and academic values.

At the level of governance, the results suggest that effective AI adoption requires clear institutional frameworks that define roles, responsibilities and ethical boundaries. Universities should develop AI governance policies that articulate principles around transparency, accountability, privacy and fairness, and that specify processes for stakeholder consultation and oversight (Wu et al., 2024; Tarisayi, 2024). Embedding AI-related responsibilities within existing academic boards and leadership structures, rather than relegating AI to isolated technical units, can help ensure that AI initiatives remain aligned with

institutional missions and academic standards. The positive association between AI-driven decision-making and leadership effectiveness further indicates that leaders should actively cultivate cultures of data-informed deliberation, where AI-generated evidence complements, rather than displaces, professional judgment.

For policymakers and funding agencies, the study highlights the need to move beyond purely infrastructural conceptions of digital transformation. Policies that support AI in higher education should allocate resources not only for hardware, software and connectivity, but also for leadership development, staff training and governance capacity. National and state-level initiatives could, for instance, establish cross-institutional leadership academies focused on AI and data governance, or provide incentives for collaborative projects that link AI technical expertise with leadership and educational scholarship. Such initiatives would help ensure that AI investments translate into sustainable capability building and contextually appropriate innovations.

Scholarly implications concern both theory and method. By integrating technology acceptance perspectives with digital leadership and complexity views, the study proposes and tests a model in which AI adoption operates through capability and decision-making mechanisms to shape leadership effectiveness. The strong empirical support for this model suggests that future research on AI in higher education should pay closer attention to leadership capabilities, decision processes and governance arrangements, rather than focusing exclusively on individual user acceptance or tool-specific outcomes. Methodologically, the study demonstrates the utility of PLS-SEM for modelling complex, capability-based relationships in AI and leadership research, illustrating how measurement and structural diagnostics can be used to build cumulative, predictive theory (Hair et al., 2022).

Several limitations should be acknowledged. First, the cross-sectional design precludes causal inference and does not capture temporal dynamics in AI adoption and leadership practice. Longitudinal designs could examine how changes in AI adoption, digital leadership competency and AI-driven decision-making co-evolve and how these trajectories influence leadership effectiveness over time. Second, data were collected via self-report from leaders and faculty within a single national context. Although India offers a rich and diverse higher education landscape, future studies could undertake comparative analyses across countries and regions to explore how regulatory frameworks, cultural expectations and resource conditions shape AI–leadership linkages.

Third, the study focuses on a specific configuration of constructs and does not include potentially relevant factors such as organisational culture, faculty unions, student voices or external accreditation pressures. Incorporating these dimensions could provide a more holistic understanding of the ecosystems in which AI-enabled leadership operates. Fourth, while the PLS-SEM results show very high explanatory power, the tight coupling among AI adoption, digital leadership competency and AI-driven decision-making may raise concerns about conceptual distinctiveness in some settings; future work could further refine the measurement of these constructs and explore alternative model specifications, including higher-order or formative representations of leadership competencies.

Future research can build on these findings in several directions. Longitudinal and mixed-method designs would be particularly valuable. Longitudinal surveys and panel data could trace how AI adoption and leadership capabilities develop as institutions move from pilot projects to mainstream integration, while case studies and ethnographic work could illuminate how leaders interpret and negotiate AI-related tensions in everyday practice. Experimental and quasi-experimental designs might evaluate the effects of leadership development interventions or AI governance reforms on subsequent patterns of AI use and leadership outcomes.

Cross-cultural research is also needed to examine whether and how the relationships identified here generalise to other higher education systems. Comparative studies could, for example, investigate whether the mediating roles of digital leadership competency and AI-driven decision-making hold in contexts with different regulatory regimes, funding models or academic traditions. Finally, there is scope to explore more closely the ethical and socio-political dimensions of AI-enabled leadership. Future studies could investigate how leaders balance competing values such as efficiency, equity, academic

freedom and privacy when deploying AI, and how these value choices shape trust in institutional leadership among students and staff.

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