

From Digital Foundations to Transformational Outcomes: Unveiling the Mediating Role of AI Adoption and the Boundary Role of Decision Quality

Dr Muhammad Ali ^{1*}, Dr. Lubna Shaheen²

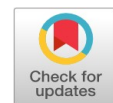
¹Institute of Management Sciences, The University of Haripur, Pakistan.

²Policy, Planning and Implementation Unit, School Education Department, Civil Secretariat, Govt. of Balochistan.

Abstract: The study investigates how organizational digital capabilities contribute to digital transformation success by examining the mediating role of artificial intelligence (AI) adoption and the moderating role of decision quality. Specifically, the study explores how digital infrastructure maturity and digital readiness influence AI adoption and how AI adoption translates these capabilities into successful digital transformation outcomes. A quantitative research design was employed, and data were collected from organizations undergoing digital transformation initiatives. The proposed structural model was empirically tested using structural equation modeling (SEM) to examine the direct, mediation, and moderation relationships among digital infrastructure maturity, digital readiness, AI adoption, decision quality, and digital transformation success. The findings demonstrate that digital infrastructure maturity and digital readiness significantly enhance AI adoption and digital transformation success. AI adoption plays a critical mediating role by translating organizational digital capabilities into transformation outcomes. Furthermore, decision quality strengthens the relationship between AI adoption and digital transformation success, indicating that organizations with superior decision-making processes derive greater value from AI-enabled initiatives. This study contributes to digital transformation and AI adoption literature by developing an integrated model that explains the mechanisms through which organizational capabilities generate transformation value. By positioning AI adoption as a key transformation pathway and decision quality as an important boundary condition, the study provides new insights into how organizations can maximize returns from AI investments and achieve sustainable digital transformation.

Keywords: Artificial intelligence adoption, Digital transformation success, Digital readiness, Digital infrastructure maturity, Decision quality, Structural equation modeling.

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INTRODUCTION

Digital transformation has rapidly evolved from a strategic option into an operational necessity for organizations navigating highly competitive and technologically dynamic environments. Over the past decade, the convergence of artificial intelligence (AI), data analytics, cloud computing, and automation has fundamentally reshaped organizational processes, decision-making structures, and operational capabilities (e.g. Rajagopal et al., 2022; Feroz & Kwak, 2024). At the center of this transformation lies AI, widely regarded as the most disruptive force of modern digitalization due to its ability to learn, predict, optimize, and enhance human capabilities at scale (Kumar et al., 2024). Organizations adopting AI-enabled systems often report improvements in productivity, agility, and innovation, positioning AI as a core driver of business resilience and competitiveness in the digital era (Ali et al., 2024). Despite the transformative potential of AI, its successful adoption remains uneven across industries, largely dependent on technological capability, organizational readiness, and the quality of strategic decisions that guide digitalization efforts.

In this fast-changing digital landscape, more businesses are realizing that AI is essential to their strategy and operations. Schmitt (2023) argues that AI can achieve great outcomes for firms with strong digital infrastructures and digitally ready workers. Due to their storage, interoperability, cloud computing, and technological backbone networks, leading digital infrastructure providers can quickly integrate AI systems (Akter et al., 2022). AI system implementation and use are accelerated by digital readiness, which includes staff skills, company culture, and strategy alignment (Fenwick et al., 2024). All of these issues affect digital transformation and AI adoption.

*Corresponding author: Dr Muhammad Ali

†Email: msali747@gmail.com

Furthermore, scalable AI integration and high-quality digital infrastructure improve operational efficiency and innovation (Bhowmick & Seetharaman, 2024). Chen et al. (2025) discovered that digital readiness impacts analytics, automation, digital platform performance, technology adoption, and organizational learning. Generally studies in this domain acknowledge the importance of digital infrastructure and preparedness, but they often ignore the influence of AI adoption on transformation success. Furthermore, empirical research shows that AI adoption is less important than organizational decision-making in digital transformation (Ransbotham et al., 2021). Despite its relevance, high-quality decision-making has been studied little for its moderating effect on transformation success.

Existing research also highlights the importance of decision quality as a critical factor shaping digital innovation outcomes. For example, Sakthivel (2025) found that data-driven decision-making enabled by AI significantly improves firm performance by enhancing managerial judgment and enabling proactive strategic planning. Similarly, Shrestha et al. (2019) emphasized that AI augments managerial cognition, allowing organizations to leverage real-time data and predictive insights for more informed decision-making. Despite the acknowledged importance of decision quality in digital transformation contexts, surprisingly few studies have examined its moderating role in amplifying the impact of AI adoption on digital transformation success. Much of the scholarly work treats decision quality as an outcome rather than as a contextual condition that shapes the effectiveness of AI-enabled transformation. Consequently, it remains unclear whether organizations with higher-quality decision processes benefit more from AI adoption than those with weaker decision structures.

Although the literature has made significant strides in addressing the relationship between digital capability and organizational transformation, several critical gaps persist. First, existing studies rarely integrate digital infrastructure maturity, digital readiness, and AI adoption into a single structural framework (e.g. Kubilay & Celikbas, 2025; Nortje & Grobbelaar, 2020), despite evidence indicating that these elements are highly interconnected. Second, while earlier research acknowledges the significance of AI adoption in enhancing business performance (Ali et al., 2025; Hong et al., 2025), few empirical studies investigate its mediating role between organizational digital capabilities and transformation success (e.g. Aghazadeh et al., 2024). This oversight limits theoretical understanding of how digital capabilities translate into tangible transformation outcomes. Third, the role of decision quality as a moderator in the AI-to-transformation pathway remains insufficiently studied. Given that decision-making is a central mechanism through which AI produces value, ignoring this moderating relationship restricts the explanatory power of existing models. Therefore, addressing these gaps is essential for both scholars seeking to refine digital transformation theory and practitioners aiming to maximize gains from AI investments.

The gap identified above underscores the need for a comprehensive investigation into how digital capability factors specifically digital infrastructure maturity and digital readiness influence digital transformation success through AI adoption, and how decision quality strengthens this relationship. This research is significant because organizations often invest heavily in AI without achieving meaningful transformation, partly due to misalignment between technological capacity and decision-making effectiveness. By examining the mediating role of AI adoption and the moderating effect of decision quality, this study provides a more complete understanding of how organizations can optimize their digital transformation strategies and realize more substantial returns from their technological investments. Furthermore, the study contributes to technology adoption and digital transformation literature by integrating perspectives from the Technology–Organization–Environment (TOE) framework, dynamic capability theory, and AI assimilation research. To address these gaps, the study is guided by the following research questions:

1. To what extent do digital infrastructure maturity and digital readiness influence AI adoption within organizations?
2. How does AI adoption affect digital transformation success?
3. Does AI adoption mediate the relationship between digital capability factors (digital infrastructure maturity and digital readiness) and digital transformation success?
4. Does decision quality moderate the relationship between AI adoption and digital transformation success, strengthening the effect under conditions of higher decision quality?

These questions aim to uncover the mechanisms and boundary conditions that shape effective AI-driven transformation, offering theoretical depth and practical relevance.

This study addresses the above research questions by proposing and empirically testing a structural model that incorporates digital infrastructure maturity, digital readiness, AI adoption, decision quality, and digital transformation success. The model explains how foundational digital capabilities translate into transformative outcomes through AI adoption and how decision quality influences this process. By doing so, the study advances theoretical understanding of AI-enabled transformation and provides actionable insights for organizations striving to enhance their digital maturity. Practically, the findings are expected to guide policymakers, digital leaders, and managers in designing more effective AI adoption strategies, strengthening decision-making processes, and aligning digital investments with transformation goals. Theoretically, the study contributes a novel integrative model that clarifies the pathways and conditions through which AI generates organizational value, addressing an important gap in the digital transformation literature.

THEORETICAL FOUNDATIONS OF THE STUDY

Hypothesis Development

Digital Infrastructure Maturity → Digital Transformation Success: Digital infrastructure maturity refers to the extent to which an organization's digital foundation such as platforms, data systems, connectivity, and integration mechanisms is reliable, scalable, and interoperable enough to support digital initiatives across the organization (Thordsen & Bick, 2022). Organizations need a mature digital infrastructure to integrate new digital tools, platforms, and processes for digital transformation projects (Brunetti et al., 2020). A sophisticated digital infrastructure includes cloud computing, interoperable systems, high-quality data repositories, and connectivity, which helps organizations execute large-scale digital transformation programs (Verhoef et al., 2021). Mature digital infrastructure improves scalability, operational agility, and cross-functional digital activity orchestration (e.g. Block, 2023). Lack or fragmentation of core digital infrastructure makes transformation harder, more expensive, and more likely to fail (Davidson, 1993). Thus, digital infrastructure maturity determines an organization's ability to integrate digitally and transform (Gökalp & Martinez, 2022).

Furthermore, digital transformation requires organizational agility and inventiveness, and empirical evidence shows that digital infrastructure maturity promotes both (e.g. Chen et al., 2025). According to Chen et al. (2025), digital infrastructure lets organizations swiftly test new technologies, reorganize resources, and restructure processes. Fazlali et al. (2024) found that digital skilled organizations are more responsive and efficient in digital transformation. Digital transformation involves ongoing innovation, system reengineering, and technology integration, making mature infrastructure a strategic facilitator rather than a technical component (Soto et al., 2023). Digital infrastructure maturity reflects how well an organization's digital platforms, data architecture, and connectivity are developed and integrated to support digital innovation, process redesign, and transformation initiatives (Suprun et al., 2024). Businesses need adaptable tech to recognize, grab, and rearrange digital opportunities to survive digital transition (Hussain et al. (2025). Moreover, organizations with strong digital capabilities leads to greater organizational performance (Khin & Ho, 2019). Thus, the literature strongly supports the idea that digital infrastructure maturity favorably affects digital transformation success.

H1: Digital Infrastructure Maturity has a positive and significant effect on Digital Transformation Success.

Digital Readiness → Digital Transformation Success: Digital readiness reflects how prepared an organization is to adopt, use, and benefit from digital technologies in its operations and strategies (Machado et al., 2021). Organizations depend on employees' digital readiness to achieve digital transformation, as it shapes their willingness to adopt and effectively use digital technologies (Höyng & Lau, 2023; Silva et al., 2022). Digital readiness is critical for organizations as it determines their capacity to adopt, implement, and effectively utilize digital technologies (Alotaibi et al., 2025). Higher levels of digital readiness facilitate smoother digital transformation processes and contribute to improved organizational performance (Wang et al., 2025). Moreover, with the digital readiness maturity, organizations become better prepared to progress toward digital transformation, enabling the effective integration of digital technologies to redesign processes, create value, and enhance overall performance (Ghobakhloo & Iranmanesh, 2021). Digital transformation is more likely to succeed when employees are tech-savvy and operate in a creative atmosphere (Ismail et al., 2023).

Digital transformation success depends on an organization's ability to align technology adoption with workforce capabilities and organizational processes (Vial, 2021). When employees are supported with appropriate digital

skills and supportive environment, digital technologies are more effectively embedded into business operations thus leading to digital effective digital transformation (Cetindamar et al., 2021; Senadjki et al., 2024). This alignment enables organizations to realize sustainable performance improvements and long-term strategic value from digital transformation initiatives.

H2: Digital Readiness has a positive and significant effect on Digital Transformation Success.

Digital Infrastructure Maturity → AI Adoption: AI adoption refers to the extent to which an organization implements and uses artificial intelligence technologies to support decision-making, automate processes, and enhance organizational performance (Booyse & Scheepers, 2024). Digital infrastructure maturity plays a foundational role in enabling AI adoption by providing the technological and organizational conditions necessary for deploying advanced analytics and intelligent systems (e.g. Dey & Ghose, 2025). Prior research conceptualizes digital infrastructure as a scalable and modular foundation composed of platforms, data architectures, and integration mechanisms that support the deployment and coordination of digital technologies across the firm (Li et al., 2022). AI systems, in particular, depend heavily on high-quality data, reliable connectivity, interoperable systems, and computing capabilities to function effectively (Chander et al., 2022). Studies on digital transformation emphasize that organizations with mature digital infrastructures are better positioned to integrate complex technologies, such as AI, into their existing processes and workflows, whereas fragmented or legacy infrastructures significantly hinder adoption efforts (e.g. Verhoef et al., 2021).

From an AI adoption perspective, organizations require not only access to AI tools but also the infrastructural capacity to embed them into operational and decision-making routines. Davenport and Ronanki (2018) argue that successful AI adoption depends on robust data pipelines, system integration, and organizational readiness to scale AI applications beyond isolated pilots. Similarly, empirical evidence shows that firms with stronger digital and IT foundations are more likely to adopt AI technologies and realize value from them, as mature infrastructures reduce implementation complexity and support workforce interaction with intelligent systems (Dwivedi et al., 2021). Therefore, digital infrastructure maturity functions as a critical enabler that allows organizations to translate AI investments into effective adoption and meaningful organizational use, rather than treating AI as a standalone technological experiment.

H3: Digital Infrastructure Maturity positively influences AI Adoption.

Digital Readiness → AI Adoption: Digital readiness is widely recognized as a critical predictor of technology adoption, including advanced systems such as artificial intelligence (Flavián et al., 2022). Based on Technology–Organization–Environment (TOE) framework, organizational readiness which includes financial resources, human capital, and managerial support significantly influences a firm's likelihood of adopting new technologies (Baker, 2011). Such as organizations with higher readiness levels demonstrate greater capacity to assimilate digital technologies (Jewapatarakul & Ueasangkomsate, 2024). AI adoption requires substantial skill development, cultural openness to innovation, and strategic alignment all elements of digital readiness (Wang et al., 2025). As a result, organizations that are more digitally prepared are better positioned to integrate AI into their operational and strategic systems. Ciasullo et al. (2025) emphasize that firms with high readiness particularly in terms of technical skills and innovative culture are more capable of leveraging data-driven technologies. Similarly, Aboobaker & KA (2021) found that organizations with strong learning orientation are better positioned to adopt emerging technologies due to their willingness to experiment and acquire new knowledge. Since AI technologies require employees to interact with predictive systems, interpret model outputs, and adjust workflows, organizations with strong digital readiness demonstrate significantly higher adoption rates. Thus, digital readiness increases both the competence and motivation required for successful AI integration.

Digital readiness reduces organizational resistance to change, strengthens strategic alignment, and increases confidence in AI implementation (Frick et al., 2021). Gfrerer et al., (2021) found that firms with high digital readiness are more successful in adopting digital innovations due to reduced cultural barriers and enhanced managerial support. Furthermore, Ali et al. (2025) demonstrated that readiness plays a crucial role in determining whether firms can effectively implement AI technologies and extract strategic benefits from them. When organizations lack readiness whether due to inadequate skills, unclear digital strategy, or cultural resistance AI adoption efforts often fail. Therefore, digital readiness is a key antecedent enabling firms to adopt AI successfully.

H4: Digital Readiness positively influences AI Adoption.

AI Adoption → Digital Transformation Success: Artificial intelligence plays a central role in enabling digital transformation due to its ability to optimize operations, enhance decision-making, and accelerate innovation. Davenport and Ronanki (2018) argue that AI enables organizations to automate routine tasks, improve customer engagement, and generate strategic insights capabilities that directly support transformation initiatives. Similarly, Ransbotham et al. (2021) showed that organizations using AI effectively are more likely to report superior digital transformation outcomes. AI enhances operational scalability and responsiveness, allowing firms to redesign processes and business models. As digital transformation aims to fundamentally change how organizations create value, AI adoption becomes a critical driver of transformation success. A substantial body of empirical research demonstrates that AI adoption improves efficiency, innovation, and process performance key indicators of digital transformation success. Brynjolfsson and McAfee (2017) noted that AI enhances productivity by enabling intelligent automation and predictive analytics. In addition, Shrestha et al. (2019) found that AI augments managerial capabilities by improving analytical decision-making and reducing cognitive biases. These improvements strengthen both operational and strategic dimensions of digital transformation. When AI technologies are effectively adopted, they enhance customer experience, streamline workflows, and support data-driven innovation, which collectively contribute to successful transformation.

From the perspective of dynamic capabilities, AI adoption strengthens an organization's ability to sense opportunities, seize innovations, and reconfigure resources core capabilities required for digital transformation success (Ahmad, 2025). Wamba-Taguimdje et al. (2020) argues that firms integrating AI into their operations achieve superior transformation outcomes due to enhanced learning and adaptive capabilities. Furthermore, AI adoption positively influences organizational performance by improving agility and innovation capacity (Shatila, 2025). Together, these findings highlight AI adoption as a strategic mechanism that translates digital capability into transformation success.

H5: AI Adoption has a positive and significant effect on Digital Transformation Success.

AI Adoption as a Mediator between Digital Infrastructure Maturity and Digital Transformation Success: AI drives digital transformation, but a developed digital infrastructure is the foundation for AI adoption. Due to this two-way dynamic, AI adoption makes sense. Bhowmick & Seetharaman (2024) claim that mature digital infrastructure provides high-quality data, computational resources, and integrated technological conditions for AI systems to perform properly. Moreover, Ali et al. (2025) demonstrated that AI adoption boosts creativity, process automation, and decision-making, resulting in successful transformations. When infrastructure is well-developed, organizations can better utilize AI, which boosts digital transformation. The mediation logic is supported by digital transformation and dynamic capacities theory. According to Teece (2018), technology, not infrastructure, modify organizational processes and capacities, improving performance instantaneously. Infrastructure looks to increase performance indirectly by integrating and using cutting-edge technology like AI. Digital infrastructure improves transformation results by enabling AI, analytics, and automation (Sharma et al., 2024). Infrastructure maturity alone won't alter much without AI. The key to transformation success from infrastructure preparedness is AI deployment. Research on digital transformation models is revealing technology adoption's mediation role. According to Zheng (2024), digital innovation strategies are the key way IT capabilities affects company performance. These findings suggest that infrastructure indirectly affects transformation outcomes by adopting new technology. AI mediates between digital infrastructure maturity and digital transformation success. This clarifies how infrastructure capabilities can be strategic.

H6: AI Adoption mediates the relationship between Digital Infrastructure Maturity and Digital Transformation Success.

AI Adoption as a Mediator between Digital Readiness and Digital Transformation Success: Digital readiness through its components of digital skills, cultural openness, leadership support, and strategic alignment strongly influences an organization's ability to adopt advanced technologies such as artificial intelligence. According to Nair et al. (2019), readiness significantly enhances an organization's capability to assimilate emerging technologies, making it a key antecedent of adoption. However, digital readiness itself does not automatically lead to transformation success; rather, it enables the successful implementation of digital technologies that drive transformation outcomes. Frick et al. (2021) argue that organizations with high digital readiness are far more capable of adopting transformative technologies, including AI, which subsequently enhances performance. This theoretical and empirical background positions AI adoption as the mechanism through which digital readiness produces meaningful transformation

results. AI adoption plays a central role in translating readiness into operational and strategic improvements. Leyer & Schneider (2021) highlight that AI augments cognitive capabilities, enhances managerial decision processes, and automates complex tasks benefits that cannot be realized solely through readiness. Similarly, Zong & Guan (2025) found that organizations with high readiness levels achieve greater transformation outcomes only when they adopt data-driven technologies like AI and advanced analytics. This suggests that readiness provides the competencies, culture, and strategic orientation necessary for adopting AI, while AI itself generates transformation outcomes such as improved service delivery, innovation, and agility. Without AI adoption, digital readiness alone is insufficient to trigger deep structural and performance changes.

Evidence from digital innovation research demonstrates that organizational readiness often influences outcomes indirectly through technology adoption. For instance, Höyng & Lau (2023) show that readiness predicts digital transformation success primarily when it leads to the adoption of advanced digital tools. Likewise, Ali et al. (2025) emphasize that AI adoption is a critical mediator that channels organizational capabilities including readiness into dynamic performance improvements. These studies confirm that readiness does not directly produce transformation success but requires a technological conduit such as AI. Therefore, AI adoption logically mediates the relationship between digital readiness and digital transformation success, serving as the mechanism that enables organizations to translate preparedness into transformative value.

H7: AI Adoption mediates the relationship between Digital Readiness and Digital Transformation Success.

Decision Quality Moderates the Relationship between AI Adoption and Digital Transformation Success: Although AI enhances forecast accuracy, operational efficiency, and insight production, how well decision-makers use its outputs determines its worth. Kim et al. (2022) define AI as a cognitive augmentation technology that improves human judgment in robust decision-making scenarios. Firms with great decision-making capabilities make more informed, timely, and analytics-based decisions (AI-Okaily, 2025). This makes data-driven technologies like AI increasingly useful to these organizations. Based on these findings, AI-informed managerial decisions impact how well AI adoption leads to change.

Decision quality the precision, homogeneity, and analytical rigor of organizational decisions moderates the relationship between AI adoption and transformation outcomes. Teece et al. (2016) emphasize strong decision-making procedures as essential dynamic competencies to improve an organization's responsiveness and innovation. Fenwick et al. (2024) found that AI-enabled decision-making procedures help companies thrive in digital transformation. High decision quality helps organizations grasp AI-generated insights, connect them to strategic goals, and implement AI-enabled changes. Mistakes in insight interpretation or implementation might limit or even harm outcomes when decision quality is low and AI use is widespread. There is empirical evidence that decision-making moderates the effects of digital technologies. Brink et al. (2024) found that organizations with better decision-making processes benefit more from analytics and AI. Chatterjee et al., (2024) also showed that data-driven technology and good management can boost productivity and innovation. The results confirm the notion that high-quality decisions boost AI adoption's benefits to digital transformation. Decision quality amplifies the value of AI in improving processes, strategy, and organizational performance, which moderates the AI-transformation relationship.

H8: Decision Quality positively moderates the relationship between AI Adoption and Digital Transformation Success, such that the relationship becomes stronger when Decision Quality is higher.

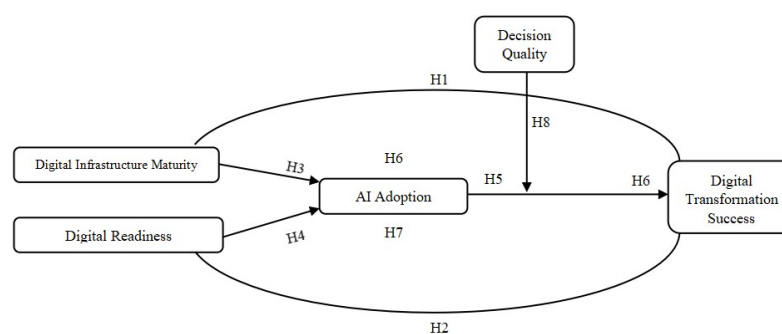


Figure 1: Conceptual Model

RESEARCH METHODOLOGY

Research Design and Approach

This study adopted a quantitative, cross-sectional research design to empirically examine the mechanisms through which organizational digital capabilities contribute to digital transformation success. A quantitative approach was considered appropriate because the study aimed to test theoretically derived relationships among multiple latent constructs, including digital infrastructure maturity, digital readiness, AI adoption, decision quality, and digital transformation success. The proposed model investigates both direct relationships and complex conditional mechanisms, including the mediating role of AI adoption and the moderating effect of decision quality. The research framework was developed based on the Technology–Organization–Environment (TOE) framework, dynamic capability theory, and AI assimilation literature. These perspectives suggest that organizations require technological foundations, organizational preparedness, and effective decision processes to successfully integrate AI and achieve digital transformation outcomes. Data were collected through a structured questionnaire survey administered to employees and managers working in organizations that had initiated digital transformation programs and adopted AI-enabled technologies. A cross-sectional design was selected because the objective was to capture current organizational practices and perceptions regarding AI adoption and digital transformation capabilities.

Population and Sampling Procedure

The target population consisted of organizations operating in technology-intensive industries where digital transformation and AI adoption have become strategic priorities. The study focused on employees working in sectors including banking, telecommunications, information technology, healthcare, manufacturing, and logistics, as these industries increasingly rely on AI-driven analytics, automation, and digital platforms.

A purposive sampling technique was employed to ensure that respondents possessed adequate knowledge of their organization's digital transformation initiatives and AI adoption practices. Respondents were required to meet two screening criteria:

1. Their organization must have implemented or planned AI-enabled digital technologies.
2. Respondents must have direct exposure to digital transformation activities, technology implementation, or organizational decision-making processes.

Data were collected from organizations located in the Gulf Cooperation Council (GCC) region, including the United Arab Emirates, Saudi Arabia, Qatar, and Oman, where substantial investments in AI and digital transformation initiatives have accelerated organizational digital maturity. A total of 450 questionnaires were distributed through online and direct organizational channels. After removing incomplete responses and eliminating invalid questionnaires, 386 usable responses were retained, representing an effective response rate of approximately 85.7%. The final sample size exceeded the minimum requirements for structural equation modeling and provided sufficient statistical power for testing direct effects, mediation, and moderation relationships.

Data Collection Procedure

Data collection was conducted over a period of three months. Before participation, respondents were informed about the purpose of the study and assured that their responses would remain confidential and would only be used for academic research purposes. Participation was voluntary, and no personal identification information was collected. To reduce common method bias, several procedural remedies were applied. First, respondents were assured of anonymity to reduce evaluation apprehension. Second, scale items measuring predictor and outcome variables were presented in a mixed order. Third, respondents were encouraged to provide honest evaluations rather than socially desirable responses.

Measurement Development

All constructs were measured using previously validated scales adapted from prior studies. A five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree was used.

Digital Infrastructure Maturity was measured using items capturing the extent to which organizational digital platforms, systems, data architecture, and technological infrastructure support digital transformation initiatives

(Gökalp & Martinez, 2022; Thordsen & Bick, 2022). Digital Readiness was measured through items assessing organizational preparedness, employee digital capabilities, technological competence, and organizational support for digital transformation (Machado et al., 2021; Gfrerer et al., 2021). AI Adoption was measured using items reflecting the extent to which organizations implement and utilize AI technologies for automation, analytics, decision support, and operational improvement (Davenport & Ronanki, 2018; Booyse & Scheepers, 2024). Decision Quality was assessed through items measuring the accuracy, analytical rigor, timeliness, and effectiveness of organizational decisions supported by digital technologies and AI-generated insights (Shrestha et al., 2019; Kim et al., 2022). Digital Transformation Success was measured using items evaluating improvements in operational efficiency, innovation, organizational agility, and value creation achieved through digital transformation initiatives (Vial, 2021; Verhoef et al., 2021).

Data Analysis Technique

The collected data were analyzed using Structural Equation Modeling (SEM). Specifically, Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed using SmartPLS 4 because the study involved multiple latent constructs, mediation analysis, and moderation testing. The analysis followed a two-stage approach:

Measurement Model Assessment: The reliability and validity of the measurement model were assessed through:

- Indicator reliability (factor loadings)
- Internal consistency reliability (Cronbach's alpha and composite reliability)
- Convergent validity (Average Variance Extracted – AVE)
- Discriminant validity (HTMT criterion)

Structural Model Assessment: The structural model was evaluated by examining:

- Path coefficients (β)
- t-values and p-values
- Coefficient of determination (R^2)
- Effect size (f^2)
- Predictive relevance (Q^2)
- Bootstrapping with 5,000 resamples

Direct effects were examined first, followed by mediation and moderation analysis. The mediating role of AI adoption between digital capability factors and digital transformation success was tested using bootstrapped indirect effects. The moderating effect of decision quality on the relationship between AI adoption and digital transformation success was examined through interaction analysis.

Common Method Bias Assessment

Because data were collected from a single survey instrument, common method bias was assessed. Harman's single-factor test was conducted, and the results indicated that no single factor accounted for the majority of variance, suggesting that common method bias was not a significant concern. Additionally, full collinearity assessment was performed, and all variance inflation factor (VIF) values remained below the recommended threshold, confirming the absence of critical common method bias.

Ethical Considerations

The study followed ethical research principles throughout the data collection process. Respondents participated voluntarily, confidentiality was maintained, and collected data were used exclusively for research purposes. No information enabling identification of individual respondents or organizations was disclosed.

RESULTS

Respondent Profile

A total of 386 valid responses were analyzed. Respondents represented organizations operating in technology-intensive sectors, including banking, telecommunications, information technology, healthcare, manufacturing, and logistics. Table 1 presents the demographic characteristics of respondents.

Table 1: Respondent Profile (N = 386)

Characteristics	Category	Frequency	Percentage
Gender	Male	248	64.2%
	Female	138	35.8%
Age	Below 30 years	82	21.2%
	31–40 years	161	41.7%
	41–50 years	102	26.4%
	Above 50 years	41	10.6%
Education	Bachelor Degree	156	40.4%
	Master Degree	184	47.7%
	Doctorate	46	11.9%
Experience	Less than 5 years	74	19.2%
	5–10 years	168	43.5%
	More than 10 years	144	37.3%

Table 1 shows the demographic results indicate that respondents possessed adequate professional experience and educational background to evaluate organizational digital transformation initiatives. The majority of respondents were between 31 and 50 years old (68.1%), while approximately 81% had more than five years of professional experience, suggesting that participants were sufficiently knowledgeable about organizational technology adoption and transformation practices.

Descriptive Statistics and Normality Assessment

Table 2: Descriptive Statistics

Construct	Mean	SD	Skewness	Kurtosis
Digital Infrastructure Maturity	3.89	0.71	-0.42	0.36
Digital Readiness	3.96	0.68	-0.51	0.41
AI Adoption	3.82	0.76	-0.39	0.29
Decision Quality	3.91	0.73	-0.46	0.33
Digital Transformation Success	4.01	0.69	-0.55	0.48

Table 2 presents the descriptive statistics for all study constructs. The mean values indicate that respondents generally perceived their organizations as moderately high in digital capability, AI adoption, and transformation success. All skewness and kurtosis values were within acceptable limits (± 2), confirming that the data distribution was appropriate for SEM analysis.

Measurement Model Assessment

The measurement model was evaluated by examining indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Following recommended procedures for PLS-SEM, factor loadings, Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE) were assessed.

Table 3: Measurement Model Assessment

Construct	Items	Loading Range	Cronbach's α	Composite Reliability (CR)	AVE
Digital Infrastructure Maturity (DIM)	DIM1–DIM5	0.742–0.861	0.887	0.918	0.691
Digital Readiness (DR)	DR1–DR5	0.756–0.873	0.901	0.927	0.718
AI Adoption (AIA)	AIA1–AIA5	0.771–0.882	0.913	0.936	0.746
Decision Quality (DQ)	DQ1–DQ5	0.735–0.856	0.876	0.909	0.668
Digital Transformation Success (DTS)	DTS1–DTS5	0.764–0.895	0.921	0.941	0.762

Table 3 shows the results confirm the reliability and validity of the measurement model. All factor loadings exceeded the recommended threshold of 0.70, indicating satisfactory indicator reliability. Cronbach's alpha and composite reliability values for all constructs were above 0.70, demonstrating strong internal consistency reliability. Furthermore, all AVE values exceeded the recommended minimum value of 0.50, confirming adequate convergent validity.

Discriminant Validity Assessment

Discriminant validity was assessed using the heterotrait–monotrait ratio (HTMT) criterion.

Table 4: HTMT Discriminant Validity

Constructs	DIM	DR	AIA	DQ	DTS
DIM	—				
DR	0.762	—			
AIA	0.784	0.801	—		
DQ	0.641	0.688	0.721	—	
DTS	0.756	0.773	0.824	0.705	—

Table 4 shows that All HTMT values were below the recommended threshold of 0.85, confirming that the constructs were empirically distinct from each other. Therefore, discriminant validity was established.

Structural Model Assessment and Hypothesis Testing

After establishing the reliability and validity of the measurement model, the structural model was assessed. Bootstrapping with 5,000 resamples was performed to determine the significance of hypothesized relationships.

Table 5: Direct Effects and Hypothesis Testing

Hypothesis	Relationship	β	t-value	p-value	Decision
H1	Digital Infrastructure Maturity → Digital Transformation Success	0.214	4.562	<0.001	Supported
H2	Digital Readiness → Digital Transformation Success	0.238	5.041	<0.001	Supported
H3	Digital Infrastructure Maturity → AI Adoption	0.327	7.214	<0.001	Supported
H4	Digital Readiness → AI Adoption	0.391	8.563	<0.001	Supported
H5	AI Adoption → Digital Transformation Success	0.421	9.236	<0.001	Supported
H8	Decision Quality × AI Adoption → Digital Transformation Success	0.167	3.824	<0.001	Supported

Table 5 shows the structural model results provide strong support for all hypothesized direct relationships. First, Digital Infrastructure Maturity significantly influenced Digital Transformation Success ($\beta = 0.214$, $t = 4.562$, $p < 0.001$), supporting H1. This indicates that organizations with stronger digital infrastructure are better positioned to achieve successful transformation outcomes because mature technological foundations enable integration, scalability, and operational improvements. Second, Digital Readiness positively affected Digital Transformation Success ($\beta = 0.238$, $t = 5.041$, $p < 0.001$), supporting H2. This finding highlights the importance of employee capabilities, organizational culture, and strategic preparedness in realizing transformation benefits. Third, Digital Infrastructure Maturity significantly enhanced AI Adoption ($\beta = 0.327$, $t = 7.214$, $p < 0.001$), supporting H3. This suggests that advanced digital infrastructure provides the technological foundation required for successful AI implementation. Fourth, Digital Readiness demonstrated the strongest influence on AI Adoption ($\beta = 0.391$, $t = 8.563$, $p < 0.001$), supporting H4. Organizations with higher readiness levels are more capable of integrating

AI because they possess stronger digital skills, supportive culture, and strategic alignment. Finally, AI Adoption significantly improved Digital Transformation Success ($\beta = 0.421$, $t = 9.236$, $p < 0.001$), supporting H5. This confirms that AI functions as a strategic mechanism through which organizations enhance innovation, efficiency, and transformation outcomes.

Coefficient of Determination (R^2) and Predictive Relevance

Table 6: Explained Variance and Predictive Relevance

Endogenous Construct	R^2	Q^2
AI Adoption	0.462	0.341
Digital Transformation Success	0.618	0.417

Table 6 presents the model explains 46.2% of the variance in AI Adoption through digital infrastructure maturity and digital readiness. Furthermore, digital infrastructure maturity, digital readiness, AI adoption, and decision quality explain 61.8% of the variance in Digital Transformation Success, indicating substantial explanatory power. The Q^2 values were greater than zero, confirming the model's predictive relevance.

Interpretation of Mediation Results

The mediation results demonstrate that AI Adoption serves as an important mechanism through which organizational digital capabilities contribute to digital transformation success. For H6, the indirect effect of Digital Infrastructure Maturity on Digital Transformation Success through AI Adoption was significant ($\beta = 0.138$, $t = 4.921$, $p < 0.001$), with a confidence interval ranging from 0.084 to 0.197. Since the confidence interval does not include zero, the mediation effect is confirmed. This finding indicates that mature digital infrastructure does not only directly enhance transformation outcomes but also creates value by enabling organizations to successfully adopt and utilize AI technologies. In other words, digital infrastructure provides the technological foundation, while AI adoption converts this capability into meaningful transformation outcomes. For H7, AI Adoption significantly mediated the relationship between Digital Readiness and Digital Transformation Success ($\beta = 0.165$, $t = 6.137$, $p < 0.001$). The confidence interval [0.103, 0.228] confirms the significance of the indirect effect. This suggests that organizational readiness alone is insufficient to achieve successful transformation; rather, readiness generates value when organizations translate their skills, culture, and strategic alignment into effective AI adoption. Overall, these findings support the proposed theoretical argument that AI adoption acts as a technological bridge connecting organizational capabilities with digital transformation success. The results extend digital transformation literature by demonstrating that digital capabilities create transformation value primarily through successful AI assimilation.

Total Effects and Mediation Type Assessment

Table 7: Total Effects and Mediation Classification

Relationship	Direct Effect (β)	Indirect Effect (β)	Total Effect (β)	Mediation Type
Digital Infrastructure Maturity $\rightarrow$ DTS	0.214	0.138	0.352	Partial Mediation
Digital Readiness $\rightarrow$ DTS	0.238	0.165	0.403	Partial Mediation

Table 7 shows the results indicate that AI Adoption provides partial mediation for both relationships. The direct effects of Digital Infrastructure Maturity and Digital Readiness on Digital Transformation Success remained significant after introducing AI Adoption into the model. Therefore, organizational digital capabilities influence transformation outcomes through two pathways: A direct pathway, where digital infrastructure and readiness independently contribute to transformation success. An indirect pathway, where these capabilities enhance AI adoption, which subsequently improves transformation outcomes. These findings suggest that organizations should not view AI adoption as an isolated technological investment. Instead, AI generates maximum value when supported by mature digital infrastructure and strong organizational readiness.

Moderation Analysis: The Moderating Role of Decision Quality

This study proposed that Decision Quality strengthens the relationship between AI Adoption and Digital Transformation Success. To test this moderating effect, an interaction term (AI Adoption $\times$ Decision Quality) was created and analyzed using the bootstrapping procedure with 5,000 resamples in PLS-SEM. The moderating effect was assessed by examining the significance of the interaction coefficient and the changes in explanatory power (ΔR^2) after including the interaction term.

Table 8: Moderation Analysis Results

Hypothesis	Interaction Effect	β	t-value	p-value	Decision
H8	AI Adoption $\times$ Decision Quality $\rightarrow$ Digital Transformation Success	0.167	3.824	<0.001	Supported

Table 8 shows the results indicate that the interaction between AI Adoption and Decision Quality has a significant positive effect on Digital Transformation Success ($\beta = 0.167$, $t = 3.824$, $p < 0.001$). Therefore, H8 is supported, confirming that Decision Quality significantly moderates the relationship between AI Adoption and Digital Transformation Success. This finding demonstrates that the benefits of AI adoption are not automatic but depend on the organization's ability to interpret AI-generated information and convert technological insights into effective managerial decisions. Organizations with higher decision quality are better able to utilize AI outputs, align AI-driven insights with strategic objectives, and implement transformation initiatives effectively.

DISCUSSION

This study aimed to examine how organizational digital capabilities contribute to digital transformation success by investigating the roles of digital infrastructure maturity, digital readiness, AI adoption, and decision quality. The findings provide empirical evidence that successful digital transformation is not solely dependent on technological investment but emerges from the interaction between organizational capabilities, AI assimilation, and effective managerial decision-making. The results support the proposed structural model and extend existing digital transformation literature by explaining the mechanisms through which digital capabilities generate transformation outcomes. The findings first demonstrate that digital infrastructure maturity positively influences digital transformation success (H1). This result indicates that organizations with advanced digital platforms, integrated systems, reliable data architectures, and scalable technological foundations are better positioned to achieve successful transformation outcomes. This finding aligns with Gökalp and Martinez (2022), who emphasized that digital maturity reflects an organization's ability to integrate technological capabilities to support transformation initiatives. Similarly, Thordsen and Bick (2022) highlighted that digital platforms and infrastructure capabilities represent essential foundations for achieving digital maturity. Therefore, the findings confirm that digital infrastructure should be viewed not merely as technical support but as a strategic capability enabling organizational transformation.

The results also confirm that digital readiness positively affects digital transformation success (H2). This finding suggests that technological resources alone are insufficient unless organizations possess the necessary human capabilities, organizational culture, and strategic alignment required for effective transformation. The result supports Machado et al. (2021), who argued that organizational readiness determines the extent to which firms can effectively implement digital technologies. Likewise, Gfrerer et al. (2021) emphasized that differences in managerial and employee readiness significantly influence digital transformation outcomes. Thus, the findings demonstrate that organizations must develop both technological and human readiness to maximize the benefits of digital transformation. Furthermore, the study found that digital infrastructure maturity significantly enhances AI adoption (H3). This result highlights the importance of technological foundations in enabling successful AI implementation. AI systems require high-quality data, integrated digital platforms, and reliable technological environments to function effectively. The finding supports Davenport and Ronanki (2018), who noted that successful AI implementation depends on organizational capabilities such as data availability, technological integration, and operational readiness. Similarly, Booyse and Scheepers (2024) emphasized that organizational conditions influence the successful adoption of AI-based decision-making systems. Therefore, mature digital infrastructure provides the necessary foundation for organizations to move beyond experimentation and achieve meaningful AI utilization.

The findings further reveal that digital readiness positively influences AI adoption (H4). This relationship

indicates that organizations with stronger digital skills, supportive cultures, and strategic commitment are more capable of integrating AI technologies. The result is consistent with Machado et al. (2021), who demonstrated that organizational readiness facilitates technology implementation, and Gfrerer et al. (2021), who highlighted the importance of employee and managerial preparedness in digital transformation contexts. These findings reinforce the argument that AI adoption is not purely a technological decision but requires organizational willingness, capabilities, and alignment. The study also confirms that AI adoption significantly improves digital transformation success (H5). This finding supports the argument that AI acts as a strategic enabler by improving automation, analytics capability, decision support, and organizational agility. Previous research has similarly emphasized that AI enables organizations to enhance operational efficiency and generate new sources of value. Davenport and Ronanki (2018) explained that AI creates organizational benefits through automation, cognitive insights, and customer-oriented applications. Likewise, Verhoef et al. (2021) highlighted that digital transformation success depends on organizations' ability to integrate advanced technologies to redesign processes and create value. Thus, this study confirms AI adoption as a critical mechanism through which organizations achieve transformation objectives.

The mediation analysis provides additional theoretical insight by demonstrating that AI adoption mediates the relationships between digital infrastructure maturity and digital transformation success (H6), and between digital readiness and digital transformation success (H7). These findings indicate that organizational capabilities do not automatically generate transformation benefits; rather, their value is realized when they facilitate effective AI adoption. This supports the perspective of dynamic capability theory, where organizations must transform existing resources into valuable capabilities through effective technology integration. As highlighted by Teece (2018), competitive advantages emerge when organizations are able to sense opportunities, adopt appropriate technologies, and reconfigure resources. Therefore, AI adoption represents the critical pathway through which digital capabilities are converted into transformation outcomes. Finally, the findings confirm that decision quality strengthens the relationship between AI adoption and digital transformation success (H8). This result demonstrates that the organizational value of AI depends not only on technological implementation but also on how effectively managers interpret and utilize AI-generated insights. The finding supports Shrestha et al. (2019), who argued that AI changes organizational decision structures by augmenting managerial capabilities rather than replacing human judgment. Similarly, Kim et al. (2022) emphasized that augmented intelligence enhances decision-making effectiveness by combining human expertise with AI capabilities. Therefore, organizations with stronger decision-making processes are better positioned to translate AI capabilities into successful transformation outcomes. Overall, the findings contribute to digital transformation research by presenting an integrated model that explains how and when AI creates organizational value. While previous studies have examined digital capabilities, AI adoption, or transformation outcomes separately, this study demonstrates that digital infrastructure maturity and digital readiness influence transformation success primarily through AI adoption, while decision quality determines the extent to which AI benefits are realized. The findings provide a more comprehensive understanding of AI-enabled transformation by highlighting the combined importance of technological capability, organizational preparedness, AI assimilation, and managerial decision effectiveness.

THEORETICAL AND MANAGERIAL IMPLICATIONS

Theoretical Implications

This study provides several theoretical contributions to the digital transformation and artificial intelligence adoption literature.

First, the study extends existing digital transformation research by developing an integrated framework that combines digital infrastructure maturity, digital readiness, AI adoption, decision quality, and digital transformation success. Previous studies have often examined digital capabilities and transformation outcomes separately; however, this study demonstrates how organizational capabilities are translated into transformation outcomes through AI adoption. By positioning AI adoption as a mediating mechanism, the study provides a more comprehensive explanation of how organizations convert technological and organizational resources into digital transformation value.

Second, this study contributes to the Technology–Organization–Environment (TOE) framework by demonstrat-

ing the complementary roles of technological and organizational factors in AI-enabled transformation. The findings show that digital infrastructure maturity represents a technological foundation, whereas digital readiness represents an organizational capability that enables AI adoption and transformation success. This provides empirical support for the argument that successful technology adoption depends on the alignment between technological resources and organizational preparedness.

Third, the study extends dynamic capability theory by identifying AI adoption as a key capability through which organizations transform existing resources into strategic outcomes. While digital infrastructure and readiness provide the necessary foundations, these resources create value only when organizations successfully integrate AI into operational and decision-making processes. Therefore, this study advances the understanding of digital transformation by showing that AI adoption represents an important capability for sensing opportunities, leveraging digital resources, and achieving transformation outcomes.

Fourth, this study contributes by introducing decision quality as an important boundary condition in the AI adoption–digital transformation relationship. Existing research has primarily focused on AI adoption as a direct driver of organizational outcomes, whereas this study demonstrates that the value generated from AI depends on managerial ability to interpret and utilize AI-generated insights. The moderating role of decision quality highlights that AI technologies create greater value when supported by effective analytical and strategic decision-making processes.

Managerial Implications

The findings provide important practical implications for managers and organizational leaders seeking to achieve successful AI-enabled digital transformation.

First, managers should prioritize the development of digital infrastructure maturity before implementing advanced AI solutions. Organizations should invest in integrated digital platforms, reliable data systems, cloud capabilities, and interoperable technologies because these foundations determine whether AI applications can be effectively deployed and scaled. Simply acquiring AI technologies without adequate infrastructure may limit their potential value.

Second, organizations should focus on improving digital readiness among employees and organizational units. The findings demonstrate that employee capabilities, technological confidence, and organizational openness toward digital change significantly influence AI adoption. Therefore, managers should implement continuous digital training programs, encourage technology-oriented cultures, and align digital transformation strategies with workforce capabilities.

Third, organizations should approach AI adoption as a strategic transformation capability rather than a standalone technological investment. Managers should identify business processes where AI can generate meaningful value, integrate AI into operational workflows, and ensure that AI applications support organizational objectives. Effective AI adoption requires alignment between technology implementation and business strategy.

Fourth, managers should strengthen decision quality mechanisms to maximize the benefits of AI adoption. Organizations should establish data-driven decision processes, develop analytical capabilities among managers, and create systems that combine AI-generated insights with human expertise. The findings suggest that organizations with stronger decision-making capabilities achieve greater transformation benefits from AI investments.

Finally, policymakers and industry leaders should support AI transformation by developing digital capability-building initiatives. Programs focused on digital infrastructure development, workforce skills enhancement, and responsible AI implementation can help organizations overcome barriers and achieve sustainable digital transformation.

LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Despite providing valuable insights, this study has several limitations that provide opportunities for future research.

First, the study adopted a cross-sectional research design, which limits the ability to establish causal relationships among the variables. Although the proposed relationships are supported theoretically and empirically, future studies could employ longitudinal designs to examine how digital capabilities, AI adoption, and transformation outcomes evolve over time.

Second, the study relied on self-reported survey data, which may introduce potential common method bias. Future research could incorporate multiple data sources, such as combining employee perceptions with organizational performance indicators, managerial assessments, or objective digital transformation metrics.

Third, the study examined AI adoption as a general construct without distinguishing between different AI applications. Future research could explore whether specific AI technologies, such as predictive analytics, generative AI, intelligent automation, or machine learning systems, produce different transformation outcomes.

Fourth, this research focused on organizations operating in technology-intensive sectors. Future studies could extend the model across different industries, geographical contexts, and organizational sizes to examine whether the relationships remain consistent across different environments.

Fifth, future research may consider additional contextual factors that influence AI-enabled transformation. Variables such as digital leadership, organizational culture, employee AI literacy, cybersecurity capability, and ethical AI governance could provide deeper insights into the conditions under which AI adoption generates organizational value.

Finally, future studies could extend the current framework by examining alternative outcomes of AI-enabled transformation, including organizational resilience, innovation performance, sustainability performance, and competitive advantage. Such investigations would further clarify the long-term strategic implications of AI adoption in organizations.

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