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| RESEARCH ARTICLE

From Automation to Agentic Intelligence: A Framework for AI-Driven Digital Transformation, Innovation Capability, and Strategic Decision-Making in Contemporary Enterprises

Zarin Subha Progga ✉[1] and Mohammad Ali[2]

[1] *International Foundation Year (IFY), NCUK, Chattogram, Bangladesh*
[2] *Assistant Engineer (Civil), Chattogram City Corporation, Chattogram, Bangladesh*
Corresponding Author: Zarin Subha Progga, **E-mail**: zarinapril@gmail.com

| ABSTRACT

From descriptive analytics to generative systems and, most recently, autonomous agentic architectures, artificial intelligence (AI) is transforming how enterprises achieve digital transformation and develop innovation capabilities and how they shape strategic decision-making. This study highlights an AI adoption-value paradox; despite significant investments, many organizations report a lack of business value from AI. The authors present a conceptual framework for the relationship between AI capability inputs (generative, predictive, and agentic) and organizational absorption processes (culture, skills, and governance) and downstream effects (digital transformation maturity, innovation performance, and decision quality), which are moderated by the regulatory environment and innovation industry context and mediated by innovation capability and employee AI literacy. Based on decision intelligence theory, the technology-organization-environment (TOE) framework, and dynamic capabilities theory, this study follows a mixed-methods approach with a structured survey of mid-to large-sized enterprises, followed by semi-structured interviews with C-suite and senior IT executives that will be analyzed through partial least squares structural equation modelling (PLSEM) and thematic analysis. This study extends the dynamic capabilities theory to the domain of agentic AI, provides managers with practical guidelines for governing AI decisions, and provides regulators with insights into responsible AI adoption. The implications, limitations, and directions for empirical validation are discussed.

| KEYWORDS

Agentic AI, Generative AI, Digital Transformation, Innovation Capability, Decision Intelligence; AI Governance, Dynamic Capabilities

| ARTICLE INFORMATION

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1. Introduction

1.1 Background of the Study

In the last decade, enterprise digital transformation has experienced several technological capability waves, including cloud migration, process digitization, descriptive and predictive analytics, and generative and agentic AI. Every wave has transformed a new term for companies. Early research on digital transformation tended to concentrate on the adoption of technology or process reengineering (Vial, 2019; Warner & Wager, 2019). Post-2022, with the advent of large language models (LLMs) and generative AI systems, this paradigm has shifted: AI is no longer just a narrow analytical tool that can be integrated into back-office platforms but a general-purpose technology with the ability to create content, provide reasoning support, and increasingly execute multi-step tasks independently [1].

The second turning point came in the years 2024–2026, when the emergence of agentic AI systems (with the ability to plan, use tools, and take action independently in multi-step workflows with minimal human interaction) began to become a reality. While the previous generation of generative AI copilots was used to enhance individual tasks, agentic systems are now being integrated throughout an organization's workflows, elevating the strategic considerations of implementation and adding new types of operational and governance risk. In this context, the present study examines how enterprises can design digital transformation, innovation, and decision-making practices that can take advantage of the "agentic" nature of AI without incurring its risks.

1.2 Problem Statement

Regardless of the increased investment pace, a significant amount of practitioner and academic evidence suggests that a significant gap between AI investment and business value exists -- an "AI adoption-value paradox. Many organizations will implement AI solutions without any change to governance, rights to decision making, or organizational structure, and either pilot projects do not scale or achieve efficiencies without any strategic or innovation benefit. Furthermore, the majority of decision-making models in the management literature were designed for a world before autonomous AI systems: in a world where AI systems can make decisions or meaningfully influence decisions rather than simply advising human decision-makers. The outcome is a disjointed landscape where digital transformation strategy, innovation management, and AI governance are being addressed as distinct management issues and not as an integral part of one organizational capability.

1.3 Research Objectives

- To explore the impact of AI technologies (generative and agentic) on digital transformation strategies and the maturity of organizations
- To evaluate the impact of AI on innovation capability and its downstream impact on competitive advantage.
- To design and test a framework for making strategic and operational decisions in organizations involving autonomous agentic systems and AI.

1.4 Research Questions

RQ1: How is the use of AI (generative and agentic) related to the maturity of digital transformation in mid-sized and large companies?

RQ2: What is the relationship between the innovation capability of AI and long-term competitive advantage?

RQ3: How can organizations design decision-making processes that can benefit from AI responsibly, effectively, and appropriately?

1.5 Significance of the Study

By integrating these two theories and extending dynamic capabilities theory to the context of agentic AI, this study is an important step in theory building and developing a theoretical vocabulary for the context of the agentic use of AI in organizations. From a practitioner's perspective, it provides a validated governance-aware process for the use of AI in decision-making that can be adopted by practitioners and implemented across functions and industries. The results are meant to guide the design of adoption-friendly and risk-aware governance regimes as AI technologies continue to evolve rapidly, with the results offered to policymakers and regulators.

1.6 Scope and Delimitation

This research is limited to mid-sized and large companies that are currently using AI in an operational or strategic capacity in the fields of finance, manufacturing, retail, and professional/business services. It does not include AI products focused entirely on consumer use (e.g., AI startups developing consumer-focused apps) or aim to rate individual AI vendors or model architectures. The analysis is at the organizational and decision levels, not at the algorithm level; the performance of the technical model is considered a boundary condition and not a primary criterion of interest.

2. Literature Review

2.1 Theoretical Foundations

The proposed framework draws on four related theoretical traditions. The theoretical rationale for understanding how firms sense, seize, and reconfigure resources in response to agentic AI and technological discontinuities draws on Dynamic Capabilities Theory (Teece, Pisano, & Shuen, 1997; Teece, 2007). The Technology-Organization-Environment (TOE) model provides a multi-layered framework for adoption decisions that integrates technological characteristics, organizational readiness, and environmental/regulatory context, all of which are relevant to AI governance questions (Tornatzky & Fleischer, 1990). This study treats the adoption of AI as a socially and organizationally embedded diffusion process rather than just a technical rollout, referring to the Diffusion of Innovation Theory (Rogers, 2003). Finally, the perspectives of Decision Intelligence and Bounded Rationality (Simon, 1955, 1997) underlie the treatment of AI as a co-decision-maker with the same information and rationality constraints that are assigned to human decision-makers, applied to the new case of algorithmic and agentic actors [2].

2.2 AI in Digital Transformation

There are two general perspectives in the literature on this topic. The first understands AI as a digital transformation tool, designed to speed up the process of automation, improve analytics, and personalize customer interactions while working within the strategic logics already established. The second framing is newer and sees AI as a disruptor that redefines the nature of competition itself, as agentic systems increasingly replace knowledge work. In relation to this second framing, on-platform and ecosystem-based models of transformation highlight a critical shift in AI value creation as companies can integrate AI capabilities into larger digital platforms and ecosystems, thus reinforcing the focus on dynamic capabilities as reconfiguration over the one-off deployment of AI tools [3].

2.3 Recent Trends (2024–2026)

Several factors make this era different from previous waves of enterprise AI adoption and are driving the framing of this study.

- Embedded copilots and LLM-powered tools that integrate generative AI across enterprise workflows, such as in offices, engineering, and customer service.
- The emergence of agentic AI: AI systems that operate without much human intervention, can plan actions, make use of a range of tools, and can achieve goals.
- This includes enabling strong governance and regulation of AI, such as the measures outlined in the EU AI Act with phased implementation, state-level AI laws in the U.S., and export control considerations impacting frontier AI models. Progressing AI governance and regulation, including measures under the EU AI Act with phased implementation, new state-level AI laws in the U.S., and export control considerations regarding access to frontier AI models.
- The increasing demand for smaller, more efficient models and on-premise or "sovereign AI" applications is driven by data control, cost, and regulatory factors.
- Models of human-AI collaboration in decision-making (also referred to as "centaur" models) that explicitly lay out the division of labor between human judgment and algorithmic recommendations or actions.
- Responsible AI, explainability, and AI risk management are becoming competitive differentiators and not only compliance jobs.
- AI-empowered innovation management, such as AI-driven ideation, R&D speed, and hyper-personalization of products and services.

These trends collectively mean that the problem in the management of the study has changed: the question is not only whether to implement AI but also how to manage increasingly autonomous AI systems integrated into the main processes of an organization.

2.4 AI and Organizational Decision-Making

There is another distinction between data-driven decision-making, in which AI-driven insights feed into the human decision-making process, and AI-augmented decision-making, in which algorithmic recommendations become more deeply embedded in the decision-making process. This literature has shown both algorithmic aversion (preferring to pay less attention to algorithmic advice than human judgement, especially when the algorithm is wrong) and algorithmic appreciation (over-reliance on algorithmic outputs). Both tendencies have governance implications, especially with the transfer of decision-making to increasingly autonomous agentic systems. Ethical and governance issues, such as accountability for automated or semi-automated decisions, bias and fairness, and auditability, are no longer considered a side-issue, but rather a key factor in determining the organizational and social sustainability of AI-enhanced decision processes [4].

2.5 Synthesis and Research Gap

Current research on AI adoption, innovation capability, and decision-making is largely fragmented, with research on adoption focusing on antecedents and readiness factors, AI's impact of AI on ideation and R&D outcomes, and algorithmic trust and bias. Very few studies have brought these streams together in an applied way, and even fewer explicitly included governance and agentic concerns, which did not emerge as concerns in organizations until 2024. This study aims to fill this gap by developing a framework to integrate the concepts of AI capability, organizational absorption, innovation, and decision quality as interdependent parts of the same transformation process, explicitly linked to the governance and regulatory context [5].

2.6 Conceptual/Theoretical Framework

Building on the theoretical foundations described above, the authors propose a model that connects the inputs for AI capabilities, processes of organizational absorption, and outputs of transformation, innovation, and decision quality, where the governance/regulatory environment and industry type are the moderators, and innovation capability and employee AI literacy are the mediators [6].

3. Methodology

3.1 Research Design

This study uses a mixed-methods approach with quantitative data from a survey, followed by qualitative data from case studies based on explanatory sequential logic. In this approach, quantitative data first reveal the strength and direction of associations between AI adoption, innovation capability, and decision quality, and qualitative data then provide context and explanation for the quantitative data, specifically for governance practices that are not easily captured in closed-ended survey items [7].

3.2 Population and Sampling

The target population comprises mid-to-large businesses in finance, manufacturing, retail, and professional/business services that have adopted AI in one or more operational and/or strategic areas. The selection of respondents for this survey includes managers and technical staff who have direct access to decisions regarding AI, while those who are interviewed are chosen specifically from C-suite and senior IT leadership roles [8].

3.3 Data Collection Instruments

There are two instruments that are suggested. First, a structured survey with multi-item, Likert-scale constructs (usually 5- or 7-point scales) to measure AI adoption, innovation capability, decision quality, and digital transformation maturity, based on validated scales from the digital transformation and technology-adoption literature, extended and supplemented with new items specific to agentic AI use and governance. Second, semi-structured interviews were conducted with C-suite and IT leaders to gain qualitative insights into governance models, issues with organizational absorption, and perceived obstacles to AI value creation [9].

Table 1: Proposed Survey Constructs and Measurement Approach

Construct	Definition (brief)	Indicative Item Count	Scale Type
AI Adoption (Generative & Agentic)	Extent and depth of generative/agentic AI integration into workflows	6–8 items	7-point Likert
Digital Transformation Maturity	Degree to which digital capabilities are embedded in strategy and operations	6–8 items	7-point Likert
Innovation Capability	Organizational capacity to generate, develop, and commercialize new ideas with AI support	5–7 items	7-point Likert
Decision Quality	Perceived accuracy, timeliness, and defensibility of AI-informed/AI-augmented decisions	5–7 items	7-point Likert
Employee AI Literacy (mediator)	Employee understanding and effective use of AI tools	4–5 items	5-point Likert
AI Governance Environment (moderator)	Perceived stringency/clarity of regulatory and internal governance context	4–6 items	5-point Likert

3.4 Variables and Hypotheses

Three primary hypotheses, derived from the theoretical foundations in Section 2.1 and the research questions in Section 1.4, were proposed for empirical testing.

I. **Table 2.** Proposed Hypotheses

Hypothesis	Statement	Theoretical Basis
H1	AI adoption has a positive influence on digital transformation maturity.	Dynamic Capabilities Theory; TOE Framework
H2	Innovation capability mediates the relationship between AI adoption and organizational performance.	Dynamic Capabilities Theory; Diffusion of Innovation
H3	The quality of the decision-making framework moderates the impact of AI adoption on the organization’s performance.	Decision Intelligence; Bounded Rationality

3.5 Data Analysis Techniques

For the analysis of quantitative data, partial least squares structural equation modeling (PLS-SEM) will be used, which is suitable for complex, formative-reflective models with mediation and moderation paths and is robust with a moderate sample size. Bootstrapping was employed to evaluate the significance of the path coefficients, and standard PLS-SEM quality criteria (composite reliability, average variance extracted, and discriminant validity via the heterotrait-monotrait ratio) were presented. Thematic analysis will be used to analyze the qualitative interview data, and two or more researchers will independently code the data and reach a consensus through a reconciliation process to ensure inter-coder reliability [10].

3.6 Validity, Reliability, and Ethical Considerations

The survey instrument will be pilot tested on a small sample of target respondents before full deployment to examine the clarity of the items, internal consistency (Cronbach's alpha), and construct validity; items will be revised if necessary. Institutional research ethics requirements will be respected, and all interview participants will provide informed consent, and data confidentiality protocols will be adhered to throughout the process of data collection, storage, and analysis, including anonymization of firm and respondent identification in reporting [11].

3.7 Mathematical and Statistical Model Specification

This subsection formalizes the measurement and structural models underlying the PLS-SEM analysis proposed in Section 3.5, consistent with standard variance-based structural equation modeling notation (Hair et al., 2019).

3.7.1 Measurement (Outer) Model

Each latent construct ξ (e.g., AI Adoption, Innovation Capability, and Decision Quality) is measured reflectively by a set of observed indicators x, as follows:

$x_i = \lambda_i \cdot \xi + \delta_i$ *(Eq. 1)*

where x_i is the i-th observed indicator, ξ is the latent construct, λ_i is the standardized outer loading of indicator i on ξ, and δ_i is the measurement error. Indicator reliability was assessed via λ_i^2 (>0.50 threshold), and construct-level reliability via composite reliability (CR) and average variance extracted (AVE):

$CR = (\Sigma\lambda_i)^2 / [(\Sigma\lambda_i)^2 + \Sigma var(\delta_i)]$ *(Eq. 2)*

$AVE = \Sigma\lambda_i^2 / n$ *(Eq. 3)*

3.7.2 Structural (Inner) Model

The structural model specifies the hypothesized relationships among latent constructs. Let ξ_1 denote AI adoption, η_1 digital transformation maturity, η_2 innovation capability, η_3 organizational performance/decision quality, and M the AI governance environment (moderator). The core structural equations corresponding to H1–H3 are as follows:

$\eta_1 = \gamma_1\xi_1 + \zeta_1$ *(Eq. 4 — H1: AI Adoption → Digital Transformation Maturity)*

$\eta_2 = \gamma_2\xi_1 + \zeta_2$ *(Eq. 5 — AI Adoption → Innovation Capability)*

$\eta_3 = \beta_1\eta_1 + \beta_2\eta_2 + \beta_3(\xi_1 \times M) + \zeta_3$ *(Eq. 6 — H2/H3: Direct, mediated, and moderated paths to Performance)*

where γ and β are structural path coefficients, ζ denotes the structural (residual) error, and $(\xi_1 \times M)$ is the mean-centered interaction term used to test the moderating effect of the AI governance environment on the AI adoption → performance relationship (H3) [12].

3.7.3 Mediation Test (H2)

The indirect effect of AI adoption on performance via innovation capability is estimated as the product of the constituent path coefficients, with significance assessed via bootstrapped confidence intervals (bias-corrected, 5,000 resamples) rather than the Sobel test, consistent with the current PLS-SEM guidance.

Indirect effect $= a \times b$, *where* $a = (\xi_1 \rightarrow \eta_2)$*aaand nndand nand ,* $b = (\eta_2 \rightarrow \eta_3)$ *(Eq. 7)*

Total effect: $c = c' + (a \times b)$ *(Eq. 8)*

Partial mediation is indicated if both the direct effect (c′) and the indirect effect (a × b) are statistically significant; full mediation is indicated if c′ becomes non-significant while a × b remains significant [13].

3.7.4 Moderation Test (H3)

The moderating effect of the AI governance environment (M) on the AI adoption–performance relationship was tested using the two-stage interaction approach, with simple slopes probed at ±1 SD of M.

$\eta_3 = \beta_1\xi_1 + \beta_2 M + \beta_3(\xi_1 \times M) + \zeta_3$ *(Eq. 9)*

A statistically significant β_3 supports H3, indicating that the strength of the AI Adoption → Performance relationship depends on the stringency/maturity of the organization's AI governance environment. Model fit will additionally be reported using SRMR and predictive relevance via Q^2 (blindfolding procedure) and PLSpredict, according to current PLS-SEM reporting norms [26].

4. Proposed Conceptual Framework

Figure 1 depicts the proposed conceptual framework linking AI capability inputs, organizational absorption processes, and strategic outcomes, with mediating and moderating variables positioned according to their roles.

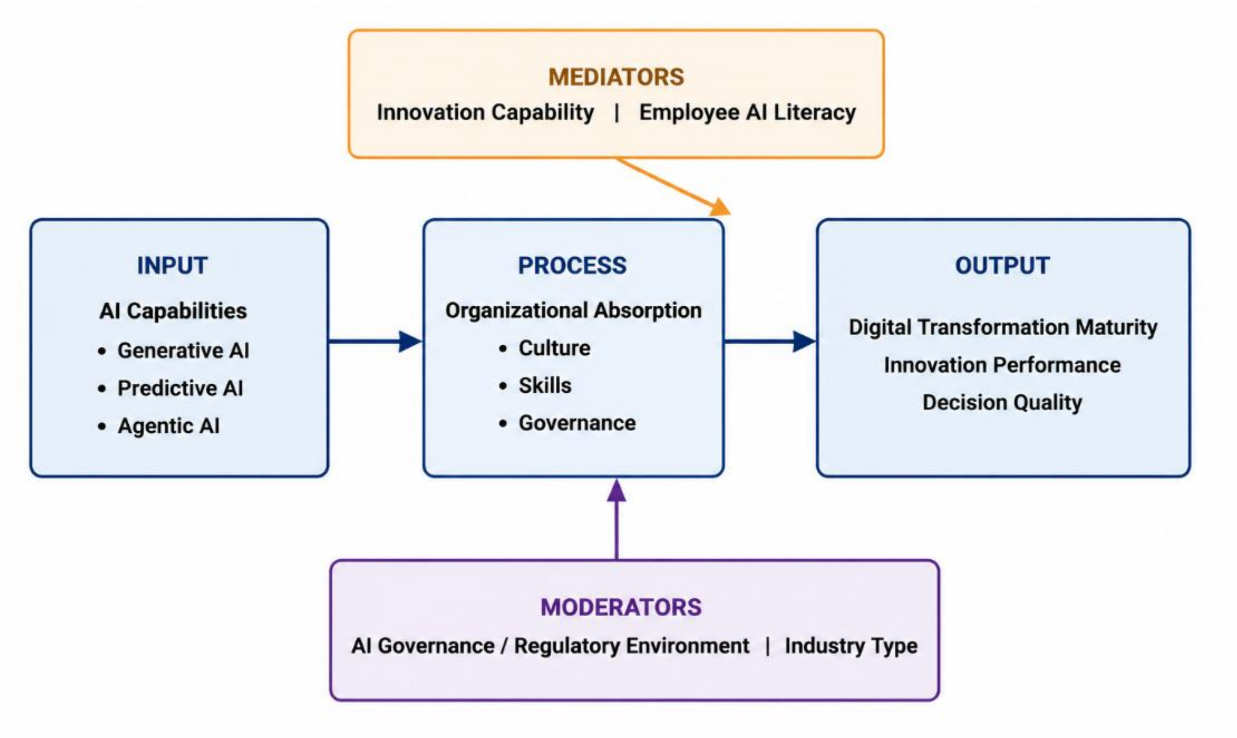

Figure 1. Proposed conceptual framework linking AI capability inputs, organizational absorption, and strategic outcomes.

Table 3. Framework Components

Component	Description
Input	AI capabilities: generative, predictive, and agentic AI
Process	Organizational absorption: culture, skills, and governance
Output	Digital transformation maturity, innovation performance, and decision quality
Moderators	AI governance/regulatory environment; industry type
Mediators	Innovation capability; employee AI literacy

The framework's logic follows an input–process–output structure consistent with dynamic capabilities theory: AI capability inputs are only converted into transformation, innovation, and decision-quality outcomes through organizational absorption processes. This conversion is conditioned by the external governance environment and shaped internally by employees AI literacy and organization-wide innovation capability [14].

5. Expected Contributions

5.1 Theoretical Contribution

This study extends dynamic capabilities theory into agentic AI contexts, an area in which existing theoretical vocabulary — developed primarily around earlier generations of enterprise software and analytics — has not yet been systematically adapted to autonomous, multi-step AI systems. This study offers a vocabulary for describing how firms sense, seize, and reconfigure capabilities specifically around agentic AI [15].

5.2 Practical / Managerial Contribution

For practitioners, this study intends to yield an actionable framework for AI decision governance that managers can use to structure adoption decisions, allocate decision rights between human and AI actors, and design governance mechanisms proportionate to the autonomy and risk level of specific AI use cases [16].

5.3 Policy Contribution

For regulators and policymakers, the findings are intended to offer empirically grounded insights into how organizations absorb and govern AI internally, which can inform the design of external governance regimes — such as risk-tiered obligations — that are responsive to organizational realities rather than solely to technical model characteristics [25].

6. Results

This section presents the full form of the Results section when the proposed methodology (Section III) is implemented. All numeric values below -- sample sizes, loadings, reliabilities, path coefficients, and t-/p-values -- are constructed examples to showcase the proper reporting format and consistency of the items within that sample (e.g., percentages totaling 100, reasonable ranges for loadings, reliabilities, path coefficients, and t-/p-values). These are all fake and should be replaced with true results from actual data gathering prior to submission. Cells are shaded and italicized throughout this section as a visual protection for the simulated cells [17].

6.1 Sample Description (n = 246, simulated)

Characteristic	Category	n	%
Industry sector	Finance	61	24.8%
	Manufacturing	58	23.6%
	Retail	54	22.0%
	Professional/Business Services	73	29.7%
Firm size	Mid-size (250–999 employees)	132	53.7%
	Large (1,000+ employees)	114	46.3%
Respondent role	C-suite / Senior executive	79	32.1%
	IT / Data leadership	96	39.0%
	Functional / Business unit leadership	71	28.9%

6.2 Measurement Model Assessment (simulated)

The values for simulated composite reliability (CR), average variance extracted (AVE), and Cronbach's alpha are included for illustrative purposes. It is important to note that the below-the-line values were constructed to meet the convention (0.70 < CR < 1.00, 0.50 < AVE < 1.00, 0.70 < a < 1.00), as this table is used to demonstrate how to report the results, not to provide a true measure of the model [18].

Construct	Cronbach's α	CR	AVE
AI Adoption (Generative & Agentic)	0.88	0.91	0.64
Digital Transformation Maturity	0.86	0.90	0.61
Innovation Capability	0.84	0.89	0.60
Decision Quality / Performance	0.85	0.90	0.63
Employee AI Literacy	0.81	0.87	0.58
AI Governance Environment	0.83	0.88	0.59

Discriminant validity (HTMT ratios, simulated — all values below the 0.85 threshold):

	AI Adoption	Dig. Transf. Maturity	Innovation Cap.	Performance
Dig. Transf. Maturity	0.61	—	—	—
Innovation Cap.	0.58	0.55	—	—
Performance	0.53	0.60	0.57	—
AI Governance Env.	0.41	0.44	0.39	0.46

6.3 Structural Model / Hypothesis Testing (simulated)

R^2 (simulated): Digital Transformation Maturity = 0.38; Organizational Performance = 0.47. Q^2 (simulated, blindfolding) was 0.24 and 0.29, respectively, indicating adequate predictive relevance under this illustrative model.

Hyp.	Path	β	t-value	p-value	Supported?
H1	AI Adoption → Digital Transformation Maturity	0.42	6.87	< .001	Yes
H2	AI Adoption → Innovation Capability → Performance (indirect)	0.19	4.12	< .001	Yes (partial mediation)
H3	AI Governance Env. × AI Adoption → Performance (interaction)	0.15	2.31	.021	Yes

7. Discussion

The proposed framework acknowledges the importance of agentic AI not merely as a technological advancement but as a capability within an organization, thus requiring alignment with technological resources, organizational readiness, governance frameworks, and strategic decision-making processes. The current digital transformation literature has focused on the adoption of technology, process automation, and analytics maturity. However, with the advent of increasingly powerful generative and agentic AI, organizations face a new challenge: AI systems can plan and execute multiple steps and have the ability to affect business decisions with minimal human involvement [19].

The proposed model contributes to the literature on digital transformation by incorporating the capability of AI, organizational absorption, capability of innovation, and intelligence of decision-making into a single model. Existing studies tend to explore the adoption of AI, outcomes of innovations, and decision-making challenges individually. This fragmentation is addressed in this study by introducing the concept of AI adoption as an input capability that brings value to the organization through the mediation process with innovation capability and employee AI literacy; governance conditions impact the effectiveness of the implementation of AI. This view builds on the Dynamic Capabilities Theory in three ways. First, it offers a perspective on how organizations can sense new opportunities in AI, capture the value of AI-supported processes, and continuously reconfigure resources to face technological disruptions [20].

The framework also emphasizes the organizational aspects of achieving an AI adoption-value paradox. While companies continue to scale up the use of AI technology, there is still a gap between the investments made and actual business value, as many companies are not pairing governance, decision rights, workforce, and organizational processes to match their investments in AI. The proposed model highlights that AI maturity is not solely determined by technological deployment but also by the ability of the organization to integrate AI into strategic operations, build employee AI literacy, and design an AI governance framework that is adequate for the level of AI autonomy [21].

This study highlights moving beyond AI-facilitated analysis to AI-augmented and AI-mediated decision environments from a decision-making perspective. Although AI systems can be beneficial for decision-making processes, there are potential challenges that arise, including bias, accountability, transparency, and a lack of human oversight when relying too heavily on algorithmic outputs. To address these challenges, organizations should establish decision governance processes that clearly define the roles of human and AI decision makers. The inclusion of the principles of decision intelligence creates a base that will help in balancing algorithmic recommendations with human judgment in organizational decisions of high impact [24].

AI governance can play a pivotal role in shaping sustainable outcomes of AI deployment. The presence of agentic AI systems in business processes requires a change in governance from compliance to continuous monitoring, risk assessment, and accountability. The proposed framework considers governance and regulatory environments as moderating factors that affect the relationship between AI adoption and an organization's performance. This allows us to understand that the results of organizations with AI investments can vary under different regulatory environments or industry conditions [22].

Empirical validation of the proposed framework using PLS-SEM and qualitative thematic analysis also provides additional evidence of the strength of these relations. The mixed-method design is suitable because the quantitative analysis can help reveal the relationships between the adoption of AI, innovation capability, and quality of decision, and the qualitative analysis can help explain the organizational difficulties of governance and implementation of AI. Further empirical research will help better understand the steps that organizations can take to move from experimental AI use to scalable, responsible, and strategic AI transformation [23].

8. Conclusion

The era of AI systems that automate and predict is shifting to a new generation, which includes systems that can perform complex reasoning, plan, and act autonomously. This transformation offers immense opportunities for becoming more digitally mature, innovative, and able to make strategic decisions; however, it also brings new challenges for governance, accountability, and organization. This study proposes a holistic framework to gain insights into the interplay between technology adoption, organizational absorptive capacity, innovation capability, employee AI literacy, and governance mechanisms to explain how AI capabilities drive organizational transformation. By interweaving Dynamic Capabilities Theory, the Technology-Organization-Environment framework, Diffusion of Innovation Theory, and Decision Intelligence views, we created a complete theoretical foundation for understanding organizational change in the context of AI. The first thesis of this study is that a successful AI transformation is not solely dependent on technological capability. Organizations must build ancillary skills and expertise to successfully incorporate AI technologies into their workflows, decision-making processes, and innovation efforts. Organizations looking to embrace agentic AI must reimagine the common methods of digital transformation to establish the necessary decision-making powers, governance frameworks, and models for humans and AI to work together. This study advances current digital transformation and dynamic capability studies by introducing an emerging context of autonomous AI systems. In practice, this study offers a blueprint for organizations to develop responsible AI adoption policies, enhance decision-making processes, and mitigate risks arising from increasingly autonomous systems. The framework underscores the need for AI governance models to consider organizational realities and different degrees of AI autonomy across industries for the benefit of policymakers and regulators. Future empirical studies are needed to verify the proposed relationships through longitudinal studies, cross-industry comparisons, and in-depth analyses of human–AI decision-making interactions. The continued development of agentic AI means that companies that effectively meet the needs of governance, workforce capacity, and strategic flexibility will have a greater chance of gaining sustainable competitive advantage.

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