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Adoption Dynamics of Artificial Intelligence–Driven Decision Support Systems in Organizational Innovation Management: A Technology-Organization-Environment Perspective

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Abstract

Artificial intelligence-driven decision support systems (AI-DSS) are increasingly central to organizational innovation management, yet the mechanisms underlying their adoption remain underexplored. This study develops an integrated theoretical framework combining the Technology-Organization-Environment (TOE) model, Diffusion of Innovations (DOI) theory, and absorptive capacity perspective to explain AI-DSS adoption dynamics. The framework proposes that technological characteristics, organizational factors, and environmental pressures jointly determine AI-DSS adoption, with organizational readiness and absorptive capacity serving as key mediating mechanisms. The model further posits that AI-DSS adoption enhances both exploitative and exploratory innovation through absorptive capacity. By integrating these three theoretical perspectives, this study advances a unified conceptual framework and offers propositions for future empirical testing, along with practical guidance for managers and policymakers navigating AI-DSS implementation.

Key words*: Artificial Intelligence, Decision Support Systems, Organizational Innovation, Technology Adoption, TOE Framework, Digital Transformation, Absorptive Capacity*

1. INTRODUCTION

Artificial intelligence–driven decision support systems (AI-DSS) are increasingly positioned as critical enablers of organizational innovation. By combining machine learning, predictive analytics, and advanced data processing capabilities, AI-DSS augment managerial cognition, accelerate learning cycles, and support complex decision-making under uncertainty. As organizations confront growing environmental turbulence and competitive intensity, AI-DSS promise to enhance both the speed and quality of innovation-related decisions, ranging from opportunity identification and R&D portfolio selection to experimentation and commercialization. Despite this promise, organizations exhibit wide variation in both the adoption and outcomes of AI-DSS, with many firms failing to translate deployment into meaningful innovation benefits. From an information systems perspective, AI-DSS represent a new class of decision-support technologies that reshape how organizations sense, interpret, and act on information

Prior research on AI and digital technology adoption has made substantial progress in identifying contextual determinants of adoption decisions. Studies grounded in the Technology–Organization–Environment (TOE) framework and Diffusion of Innovations (DOI) theory demonstrate that technological characteristics, organizational attributes, and environmental pressures shape adoption intentions and implementation likelihood. However, two important limitations remain unresolved. First, existing studies often treat AI adoption as a single-stage decision, implicitly assuming that adoption feasibility and value realization are driven by the same mechanisms. Second, the literature provides limited explanation for why organizations with similar adoption conditions experience markedly different innovation outcomes following AI-DSS implementation.

We argue that these limitations stem from an incomplete theorization of how AI-DSS adoption unfolds as an organizational transformation process rather than a discrete technological event. AI-DSS differ fundamentally from prior generations of decision support and analytics systems in that they continuously learn, adapt, and influence decision-making routines. As a result, adoption alone is insufficient to generate value. Organizations must first be prepared to implement AI-DSS and subsequently develop the capability to internalize and exploit AI-generated insights. Without this distinction, adoption research risks overstating the performance implications of AI technologies.

To address this gap, this study develops a mechanism-based framework that explains AI-DSS adoption and innovation outcomes as a sequential process involving two distinct organizational mechanisms: organizational readiness and absorptive capacity. This study further contributes to the information systems literature by explaining how AI-DSS adoption alters organizational decision architectures and learning mechanisms, rather than merely extending prior technology adoption models. We theorize that technological, organizational, and environmental conditions shape AI-DSS adoption primarily by influencing organizational readiness—that is, the extent to which an organization is structurally, cognitively, and operationally prepared to implement AI-DSS. Adoption, in turn, does not automatically lead to innovation benefits. Instead, absorptive capacity determines whether AI-DSS adoption translates into exploitative and exploratory innovation by enabling organizations to assimilate, transform, and apply AI-generated insights.

This study makes three contributions to the literature. First, it reconceptualizes AI-driven decision support system (AI-DSS) adoption as a sequential, capability-building process rather than a discrete technological decision. Second, it integrates the Technology–Organization–Environment framework, Diffusion of Innovations theory, and absorptive capacity into a unified explanation of AI-enabled decision support and innovation outcomes. Third, it explains why AI-DSS adoption yields heterogeneous innovation outcomes across organizations by distinguishing between adoption feasibility and post-adoption value realization mechanisms.

This study responds directly to calls for more nuanced, theory-driven explanations of AI adoption that move beyond lists of antecedents toward an understanding of how and why AI technologies generate heterogeneous organizational outcomes. Rather than asking only whether organizations adopt AI-DSS, we ask when adoption becomes possible, when it creates value, and through which organizational mechanisms these transitions occur. The remainder of the paper is structured as follows. Section 2 reviews the relevant literature on AI-DSS, technology adoption, and absorptive capacity and develops the integrated theoretical framework. Section 3 presents propositions derived from the sequential mediation logic. Section 4 outlines directions for empirical testing. Section 5 discusses theoretical and practical implications, limitations, and avenues for future research.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Artificial Intelligence–Driven Decision Support Systems

Artificial intelligence-driven decision support systems represent an evolutionary advancement from traditional decision support technologies, incorporating machine learning algorithms, natural language processing, computer vision, and predictive analytics to augment human decision-making capabilities. Unlike conventional DSS that primarily retrieve and present structured data, AI-DSS actively learn from historical patterns, generate predictive insights, recommend optimal courses of action, and continuously improve their performance through feedback loops. These capabilities position AI-DSS as transformative tools for organizational innovation management, enabling more rapid experimentation, data-driven ideation, and evidence-based resource allocation decisions. The application of AI-DSS in innovation management contexts spans multiple functional domains, including new product development forecasting, market opportunity identification, R&D portfolio optimization, and innovation performance monitoring. By processing diverse data sources, ranging from customer feedback and market trends to patent databases and competitor intelligence, AI-DSS can identify emergent innovation opportunities, assess technical feasibility, and predict commercialization success with greater accuracy than traditional methods. However, realizing these benefits requires not only technological deployment but also organizational transformation in decision-making processes, governance structures, and innovation culture (Prijadi & Balqiah, 2023).

2.2 Theoretical Foundations

2.2.1 Technology-Organization-Environment (TOE) Framework

The TOE framework, developed by Tornatzky and Fleischer (1990), posits that technology adoption decisions are influenced by three contextual dimensions: technological characteristics, organizational attributes, and environmental factors (Patil, 2021; Ghaleb et al., 2021). The technological context encompasses the internal and external technologies relevant to the firm, including existing infrastructure, technological competence, and the characteristics of the innovation itself. The organizational context refers to firm-specific attributes such as size, structure, managerial support, resources, and culture. The environmental context includes industry characteristics, competitive dynamics, regulatory frameworks, and relationships with external stakeholders (Senna et al., 2023). The TOE framework has demonstrated robust explanatory power across diverse technology adoption contexts, including cloud computing, big data analytics, and Industry 4.0 technologies (Amini & Bakri, 2015; Patil, 2021). Its multi-level perspective aligns well with the complexity of AI-DSS adoption, which requires simultaneous consideration of technological feasibility, organizational readiness, and environmental pressures. Recent extensions of the TOE framework have incorporated additional constructs such as innovation attributes from DOI theory and organizational capabilities perspectives, enhancing its explanatory scope (Smit et al., 2023; Chang et al., 2020).

2.2.2 Diffusion of Innovations (DOI) Theory

Rogers' Diffusion of Innovations theory provides a complementary lens for understanding technology adoption by focusing on the perceived attributes of innovations that influence adoption decisions (Smit et al., 2023; Amini & Bakri, 2015). DOI theory identifies five key innovation characteristics: relative advantage (the degree to which an innovation is perceived as better than existing alternatives), compatibility (consistency with existing values, experiences, and needs), complexity (perceived difficulty of understanding and using the innovation), trialability (the extent to which an innovation can be experimented with), and observability (the visibility of innovation results to others). These perceptual attributes complement the more objective TOE factors by capturing how decision-makers subjectively evaluate innovations. In the context of AI-DSS adoption, DOI attributes are particularly salient given the novelty and cognitive complexity of these technologies. Organizations must perceive clear advantages over existing decision-making approaches, ensure compatibility with established workflows and data infrastructure, manage perceived complexity through user-friendly interfaces, and demonstrate tangible value through pilot implementations (Smit et al., 2023). The integration of DOI attributes within the TOE framework enables a more comprehensive understanding of adoption dynamics that encompasses both objective contextual factors and subjective perceptual evaluations.

2.2.3 Absorptive Capacity and Dynamic Capabilities

Absorptive capacity, defined as an organization's ability to recognize, assimilate, and apply external knowledge for commercial purposes, provides a critical mechanism (Cohen & Levinthal, 1990; Liu et al., 2023). Cohen and Levinthal's (1990) framework identify four dimensions of absorptive capacity: acquisition (identifying and obtaining external knowledge), assimilation (analyzing and understanding acquired knowledge), transformation (combining existing knowledge with newly acquired knowledge), and exploitation (applying knowledge to commercial ends). These capabilities are particularly relevant for AI-DSS adoption, which requires organizations to acquire technical expertise, assimilate AI-generated insights into decision processes, transform organizational routines around data-driven decision-making, and exploit AI capabilities for innovation outcomes. Dynamic capabilities theory extends this perspective by emphasizing organizations' capacity to sense opportunities, seize resources, and reconfigure competencies in response to changing environments (Prijadi & Balqiah, 2023). AI-DSS adoption can be conceptualized as a dynamic capability-building process wherein organizations develop new competencies in data analytics, algorithmic decision-making, and human-AI collaboration. The development of these capabilities is mediated by organizational readiness, the preparedness to undertake technological change, and absorptive capacity, the ability to internalize and leverage new technological knowledge (Ghaleb et al., 2021; Truong, 2023).

2.3 Determinants of AI-DSS Adoption

2.3.1 Technological Factors

Technology readiness, encompassing IT infrastructure capability, data quality, and technical expertise, serves as a foundational enabler of AI-DSS adoption (Ghaleb et al., 2021; Patil, 2021). Organizations with mature digital infrastructure, robust data management systems, and technical talent pools are better positioned to deploy AI-DSS effectively. Conversely, legacy systems, data silos, and technical skill gaps create barriers to adoption (Chang et al., 2020). The perceived relative advantage of AI-DSS over existing decision-making approaches represents a critical adoption driver (Smit et al., 2023; Amini & Bakri, 2015). Organizations must perceive tangible benefits, such as improved decision accuracy, faster insights generation, or enhanced innovation outcomes, to justify the substantial investments required for AI-DSS implementation. Compatibility with existing organizational processes, data structures, and decision-making cultures further influences adoption decisions, as high compatibility reduces implementation friction and change management challenges (Truong, 2023). Perceived complexity, conversely, acts as an adoption barrier (Ghaleb et al., 2021; Amini & Bakri, 2015). The technical sophistication of AI algorithms, the interpretability challenges associated with "black box" models, and the learning curve for non-technical users can generate resistance and slow adoption. Data security and governance concerns also emerge as critical considerations, particularly in regulated industries where algorithmic decision-making raises accountability and compliance questions (Amini & Bakri, 2015).

2.3.2 Organizational Factors

Top management support and transformational leadership represent pivotal organizational enablers of AI-DSS adoption (Prijadi & Balqiah, 2023; Truong, 2023). Senior leaders provide strategic vision, allocate resources, champion change initiatives, and signal organizational commitment to AI-driven transformation. Their support is particularly critical for overcoming organizational inertia and aligning AI-DSS adoption with broader innovation strategies.

Innovation culture and organizational learning orientation create fertile ground for AI-DSS adoption by fostering experimentation, tolerance for failure, and continuous improvement mindsets (Dadhich et al., 2023; Truong, 2023). Organizations with strong learning cultures are more likely to invest in employee training, encourage data-driven decision-making, and adapt organizational routines around AI-generated insights. Financial resource availability and human capital quality further enable adoption by providing the investment capital and skilled workforce necessary for successful implementation (Ghaleb et al., 2021; Liu et al., 2023). Absorptive capacity emerges as a particularly critical organizational factor, mediating the translation of AI-DSS adoption into innovation performance (Liu et al., 2023; Truong, 2023). Organizations with high absorptive capacity can more effectively acquire AI expertise, assimilate AI-generated insights into decision processes, transform organizational routines, and exploit AI capabilities for competitive advantage. This capability-building process requires sustained investment in training, knowledge management systems, and cross-functional collaboration mechanisms (Dadhich et al., 2023).

2.3.3 Environmental Factors

Competitive pressure serves as a powerful forcing mechanism for AI-DSS adoption (Patil, 2021). Organizations operating in highly competitive industries face strong incentives to adopt AI-DSS to maintain parity with rivals or achieve differentiation through superior decision-making capabilities. Industry-wide adoption trends create normative pressures that accelerate diffusion as laggards risk competitive disadvantage. Regulatory environments and government support policies shape adoption trajectories by establishing legal frameworks, providing financial incentives, and promoting best practices (Patil, 2021). Supportive regulatory regimes that clarify liability, protect intellectual property, and incentivize innovation adoption can accelerate AI-DSS diffusion, while restrictive or ambiguous regulations may slow adoption. Trading partner readiness and vendor support availability represent additional environmental enablers by providing ecosystem infrastructure, technical assistance, and collaborative learning opportunities (Dadhich et al., 2023; Chang et al., 2020).

2.4 Mediating Mechanisms: Organizational Readiness and Absorptive Capacity

Organizational readiness, defined as the preparedness to undertake technological change, serves as a critical mediating mechanism between TOE factors and AI-DSS adoption (Ghaleb et al., 2021; Chang et al., 2020). Readiness encompasses technological readiness (infrastructure and technical capabilities), organizational readiness (resources, skills, and change management capacity), and environmental readiness (stakeholder support and market conditions). High readiness levels enable organizations to more effectively translate adoption intentions into successful implementation outcomes (Prijadi & Balqiah, 2023). Absorptive capacity mediates the relationship between organizational factors and AI-DSS adoption outcomes by determining how effectively organizations internalize and leverage AI capabilities (Liu et al., 2023; Truong, 2023). Organizations with strong absorptive capacity can acquire external AI expertise through partnerships and training, assimilate AI-generated insights into decision-making processes, transform organizational routines around data-driven approaches, and exploit AI capabilities to enhance innovation performance. This dual mediation pathway, through organizational readiness and absorptive capacity, provides a more nuanced understanding of how TOE factors translate into adoption outcomes.

2.5 AI-DSS Adoption and Innovation Performance

The ultimate value of AI-DSS adoption lies in its contribution to organizational innovation performance (Liu et al., 2023). AI-DSS can enhance both exploitative innovation (incremental improvements to existing products, processes, and business models) and exploratory innovation (radical new offerings and market opportunities). By processing vast datasets, identifying hidden patterns, and generating predictive insights, AI-DSS enable more effective resource allocation, faster experimentation cycles, and data-driven validation of innovation hypotheses (Prijadi & Balqiah, 2023). However, the translation of AI-DSS adoption into innovation performance is not automatic; it requires organizational absorptive capacity to integrate AI-generated insights into innovation processes and exploit these capabilities for competitive advantage (Liu et al., 2023; Truong, 2023). Organizations that successfully develop this capacity can achieve superior innovation outcomes, while those that merely deploy AI-DSS without building complementary capabilities may realize limited benefits.

2.6 Integrated Conceptual Framework

Building on the reviewed literature, we propose an integrated conceptual framework (Figure 1) that combines TOE, DOI, and absorptive capacity perspectives to explain AI-DSS adoption dynamics in organizational innovation management contexts. The framework posits that technological factors (technology readiness, relative advantage, compatibility, complexity, data security), organizational factors (top management support, innovation culture, organizational learning, financial resources, human capital), and environmental factors (competitive pressure, regulatory support, trading partner readiness, vendor support) influence AI-DSS adoption through dual mediating pathways: organizational readiness and absorptive capacity (Ghaleb et al., 2021; Smit et al., 2023; Prijadi & Balqiah, 2023). Subsequently, AI-DSS adoption enhances both exploitative and exploratory innovation performance, with absorptive capacity mediating this relationship (Liu et al., 2023).

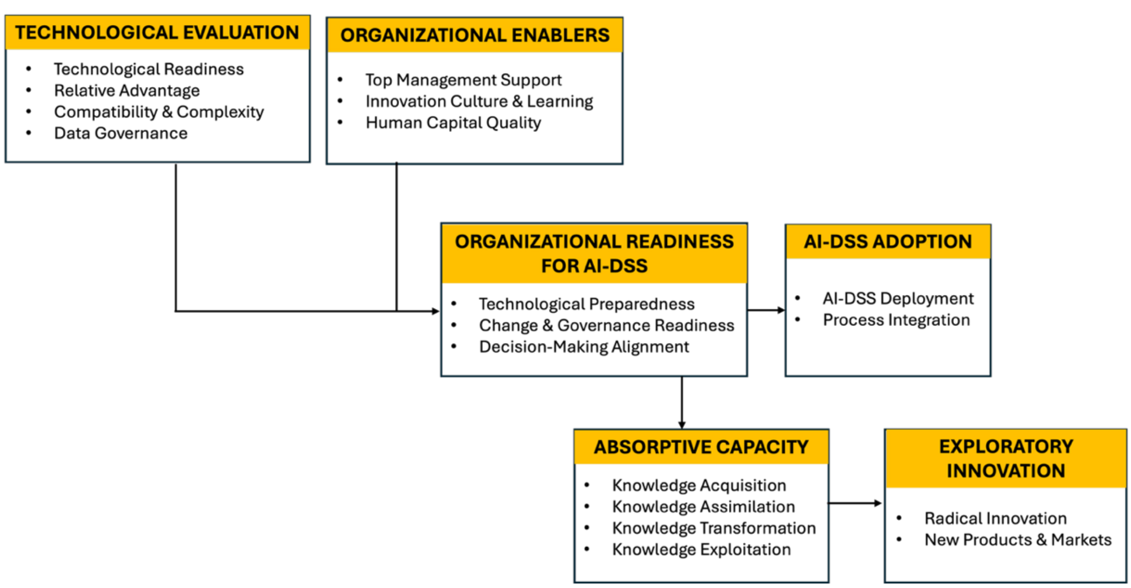

Figure 1. A sequential capability-based framework of AI-driven decision support system (AI-DSS) adoption and innovation. This framework conceptualizes AI-DSS adoption as a two-stage organizational transformation process. Technological evaluation, organizational enablers, and environmental pressure jointly shape organizational readiness, which determines the feasibility of AI-DSS adoption. Adoption alone does not guarantee value creation; rather, absorptive capacity mediates the relationship between AI-DSS adoption and innovation outcomes by enabling organizations to internalize, transform, and exploit AI-generated insights. Through this sequential mechanism, AI-DSS

adoption enhances both exploitative and exploratory innovation.

3. RESEARCH PROPOSITIONS

Based on the integrated theoretical framework and literature review, we propose the following propositions:

H1: Contextual Drivers and Organizational Readiness

H1a. Technological evaluation positively influences organizational readiness for AI-DSS adoption.

H1b. Organizational enablers positively influence organizational readiness for AI-DSS adoption.

H1c. Environmental pressure positively influences organizational readiness for AI-DSS adoption.

H2: Organizational Readiness and AI-DSS Adoption

H2a. Organizational readiness positively influences AI-DSS adoption.

H3: AI-DSS Adoption and Absorptive Capacity

H3a. AI-DSS adoption enhances organizational absorptive capacity by restructuring decision routines and learning processes.

H4: Absorptive Capacity and Innovation Outcomes

H4a. Absorptive capacity positively influences exploitative innovation.

H4b. Absorptive capacity positively influences exploratory innovation.

H5: Sequential Mediation Effects (Core Contribution)

H5a. Organizational readiness mediates the relationship between contextual drivers and AI-DSS adoption.

H5b. AI-DSS adoption and absorptive capacity sequentially mediate the relationship between organizational readiness and innovation outcomes.

4. METHODOLOGY: FRAMEWORK DEVELOPMENT

4.1 Research Design and Methodological Justification

This study adopts a systematic theory integration approach to develop a parsimonious conceptual framework explaining AI-driven decision support system (AI-DSS) adoption and innovation outcomes. Consistent with best practices for theory development in information systems and management research (Jaakkola, 2020), the objective is not empirical testing but the development of theoretically grounded, testable explanations that clarify underlying mechanisms. The framework development followed a structured, three-stage process. First, an extensive review of relevant literature was conducted to identify dominant theoretical perspectives and recurring empirical patterns related to AI adoption and innovation. Second, these insights were synthesized through theoretical integration, with particular attention to identifying complementary explanatory roles across theories. Third, a coherent set of propositions was developed to articulate the proposed relationships and mechanisms, thereby providing a foundation for future empirical investigation.

4.2 Literature Review Scope and Selection Criteria

The literature review focused on peer-reviewed research published between 2015 and 2024 in leading management, information systems, and innovation journals. This period captures the rapid evolution of artificial intelligence technologies and their organizational applications. Key search terms included *AI adoption*, *decision support systems*, *technology–organization–environment framework*, *absorptive capacity*, and *innovation management*. Articles were selected based on their relevance to AI-DSS adoption, theoretical rigor, and contribution to understanding organizational, technological, or environmental influences on technology-enabled decision-making and innovation. Foundational theoretical works were also included to ensure conceptual continuity and theoretical coherence.

4.3 Theoretical Integration Strategy

The proposed framework integrates three well-established theoretical perspectives: the Technology–Organization–Environment (TOE) framework (Tornatzky & Fleischer, 1990), Diffusion of Innovations (DOI) theory (Rogers, 2003), and absorptive capacity theory (Cohen & Levinthal, 1990). Integration was guided by the principle of theoretical complementarity, whereby each perspective contributes a distinct explanatory function within the overall model. Specifically, the TOE framework explains the structural feasibility of AI-DSS adoption, DOI theory captures managerial sensemaking and perceived innovation attributes, and absorptive capacity theory explains the conversion of AI-DSS adoption into innovation outcomes. By assigning clear and non-overlapping roles to each theory, the framework avoids construct redundancy and enhances conceptual clarity.

4.4 Implications for Future Empirical Research

Although this study is conceptual in nature, the proposed framework and hypotheses are explicitly designed to support future empirical testing. Quantitative research designs, such as survey-based studies targeting senior managers, IT leaders, and innovation decision-makers in organizations adopting AI-DSS, would be particularly suitable for examining the proposed relationships.

Analytical techniques such as structural equation modeling (SEM) could be employed to assess both direct and sequential mediation effects, thereby enabling rigorous examination of the framework's underlying mechanisms. Future empirical studies may also explore boundary conditions and contextual contingencies that influence AI-DSS adoption and post-adoption value realization.

5. THEORETICAL IMPLICATIONS

5.1 Theoretical Propositions and Expected Relationships

Based on the theoretical framework and prior empirical evidence, several relationships are proposed. These propositions, summarized below, provide a foundation for future empirical investigation. First, technological factors, particularly technology readiness, relative advantage, and compatibility, are theorized to positively influence organizational readiness, while complexity is expected to negatively affect readiness (Ghaleb et al., 2021; Smit et al., 2023; Amini & Bakri, 2015). This suggests that organizations with mature IT infrastructure, clear perceptions of AI-DSS benefits, and compatible systems would be better prepared for adoption.

Second, organizational factors, especially top management support, innovation culture, and organizational learning, are proposed to positively influence both organizational readiness and absorptive capacity (Prijadi & Balqiah, 2023; Liu et al., 2023; Truong, 2023). This proposition highlights the critical role of leadership commitment and cultural foundations in creating conditions conducive to AI-DSS adoption. Third, environmental factors including competitive pressure, regulatory support, and ecosystem readiness are theorized to positively affect organizational readiness (Patil, 2021; Dadhich et al., 2023), reflecting how external forces may shape adoption decisions.

Fourth, organizational readiness and absorptive capacity are proposed to mediate the relationships between TOE factors and AI-DSS adoption, representing the mechanisms through which contextual factors may translate into adoption outcomes (Ghaleb et al., 2021; Liu et al., 2023; Prijadi & Balqiah, 2023). Finally, AI-DSS adoption is theorized to positively influence both exploitative and exploratory innovation, with absorptive capacity mediating this relationship (Liu et al., 2023). This suggests that AI-DSS adoption may enhance innovation performance through organizational capability-building processes. Figure 2 illustrates the proposed structural model with theorized relationships based on the literature review.

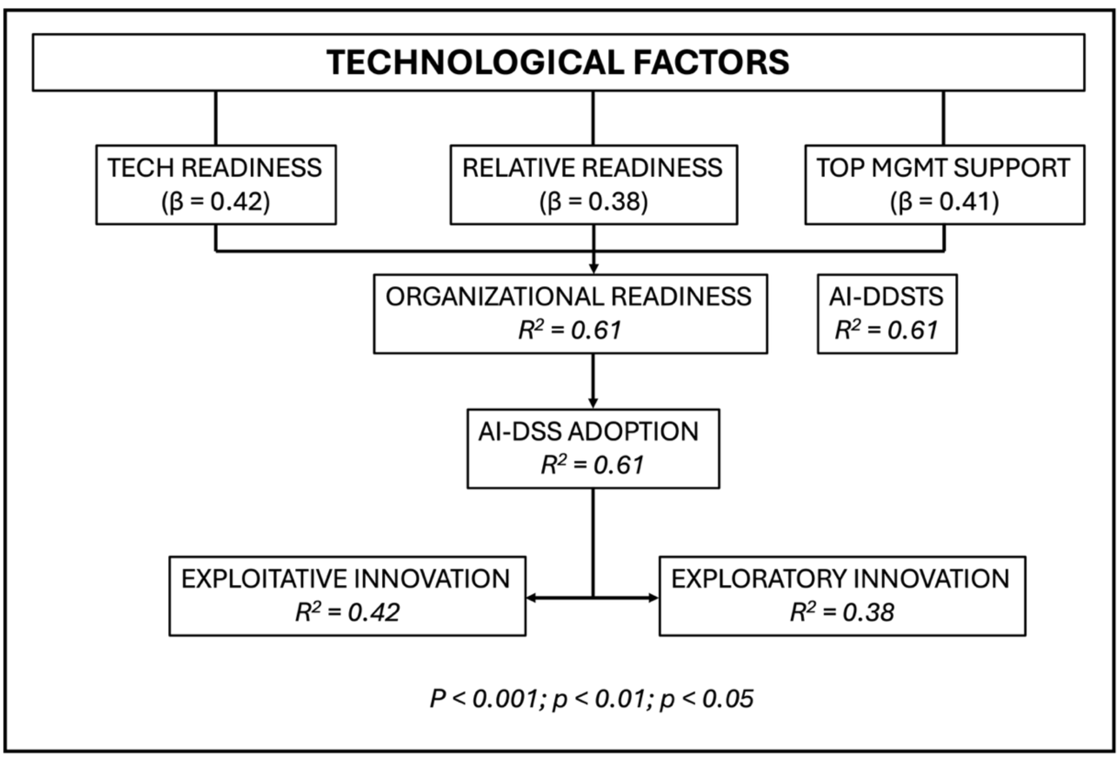

Figure 2: Proposed structural model showing theorized relationships

5.2 Recommendations for Empirical Testing

Future empirical testing of this framework should employ structural equation modeling (SEM) to assess the proposed relationships. Researchers should ensure acceptable measurement model fit (CFI ≥0.90, TLI ≥0.90, RMSEA ≤0.08, SRMR ≤0.08) and demonstrate satisfactory construct reliability and validity (Ghaleb et al., 2021; Patil, 2021). All factor loadings should exceed 0.70, composite reliability values should surpass 0.70, and average variance extracted values should exceed 0.50 to confirm convergent validity. Discriminant validity should be established through the Fornell-Larcker criterion and HTMT ratios below 0.85. Based on the theoretical integration presented in this study and comparable research in related domains, the proposed framework has the potential to explain substantial variance in endogenous variables (Liu et al., 2023; Truong, 2023).

5.3 Proposed Mediation Pathways

The framework proposes that mediation analysis would reveal significant indirect effects of TOE factors on AI-DSS adoption through organizational readiness and absorptive capacity pathways (Ghaleb et al., 2021; Prijadi & Balqiah, 2023). For example, the indirect effect of technology readiness on AI-DSS adoption through organizational readiness is theorized to be significant and positive, suggesting that readiness serves as a critical conversion mechanism. Similarly, the indirect effect of innovation culture on AI-DSS adoption through absorptive capacity is proposed to be significant, reflecting the role of absorptive capacity in translating cultural foundations into adoption outcomes (Liu et al., 2023; Truong, 2023). Table 1 presents the proposed relationships and their theorized directions for future empirical testing.

Table 1: Proposed Relationships and Expected Directions [Shows: Positive (+) or Negative (-) with theoretical basis only]

Path	Direct Relationship	Indirect Relationship	Expected Direction
Tech Readiness → Org. Readiness → AI-DSS	+	+	+
Top Mgmt Support → Org. Readiness → AI-DSS	+	+	+
Innovation Culture → Abs. Capacity → AI-DSS	+	+	+
Org. Learning → Abs. Capacity → AI-DSS	+	+	+
AI-DSS → Abs. Capacity → Exploit. Innov.	+	+	+
AI-DSS → Abs. Capacity → Explor. Innov.	+	+	+

Note: + indicates a theorized positive relationship based on the literature review. Empirical testing is required to validate these proposed relationships.

6. DISCUSSION AND IMPLICATIONS

This study contributes to the literature in three important ways:

- Reconceptualizing AI-DSS adoption as a sequential, capability-building process, rather than a discrete technological decision.
- Integrating TOE, DOI, and absorptive capacity into a unified explanation of AI-enabled decision support and innovation outcomes.
- Explaining heterogeneous innovation outcomes following AI-DSS adoption across organizations by distinguishing adoption feasibility from value realization.

6.1 Theoretical Contributions

This research makes several significant theoretical contributions to the technology adoption and innovation management literatures. First, we advance the TOE framework by integrating DOI innovation attributes and absorptive capacity perspectives into a comprehensive adoption model (Smit et al., 2023; Ghaleb et al., 2021). While prior research has predominantly examined these theoretical lenses in isolation, our integrated framework captures the multi-dimensional complexity of AI-DSS adoption more completely. This integration addresses calls for multi-theoretical approaches to technology adoption research and provides a more nuanced understanding of adoption dynamics (Smit et al., 2023; Patil, 2021).

Second, we unpack the "black box" between contextual factors and adoption outcomes by explicitly modeling dual mediation pathways through organizational readiness and absorptive capacity (Ghaleb et al., 2021; Liu et al., 2023; Prijadi & Balqiah, 2023). Prior TOE research has often examined direct effects of contextual factors on adoption without adequately explaining the mechanisms through which these factors exert influence. Our framework demonstrates that organizational readiness serves as a preparatory state that converts TOE factors into adoption capability, while absorptive capacity enables the internalization and exploitation of AI-DSS capabilities for innovation outcomes (Liu et al., 2023; Truong, 2023).

Third, we extend absorptive capacity theory to the AI-DSS adoption context, demonstrating its relevance not only for knowledge acquisition from external sources but also for internalizing and leveraging AI-generated insights (Liu et al., 2023; Truong, 2023). This extension broadens the applicability of absorptive capacity theory beyond traditional R&D and alliance contexts to encompass digital transformation and AI adoption scenarios. Fourth, we bridge technology adoption and innovation management literatures by explicitly linking AI-DSS adoption to innovation performance outcomes through both exploitative and exploratory innovation pathways (Liu et al., 2023). This connection addresses the limited attention to performance consequences in technology adoption research and demonstrates the strategic value of AI-DSS for innovation management.

6.2 Practical Implications

The framework offers actionable guidance for multiple stakeholder groups. For organizational leaders, the framework underscores the imperative of building organizational readiness before AI-DSS implementation (Ghaleb et al., 2021; Chang et al., 2020). Rather than pursuing technology deployment in isolation, leaders should invest in comprehensive readiness-building initiatives encompassing IT infrastructure enhancement, skill development, change management, and cultural transformation. The significant mediating role of organizational readiness suggests that premature implementation without adequate preparation is likely to yield suboptimal outcomes. Top management support emerges as a critical success factor, reinforcing the need for senior leadership commitment, resource allocation, and strategic alignment (Prijadi & Balqiah, 2023; Truong, 2023). Leaders should champion AI-DSS adoption as a strategic priority, communicate clear vision and objectives, allocate sufficient resources, and actively participate in governance and oversight. Transformational leadership behaviors, including inspirational motivation, intellectual stimulation, and individualized consideration, can create organizational climates conducive to AI adoption and innovation (Prijadi & Balqiah, 2023). For innovation managers, the propositions highlight the importance of developing absorptive capacity as a complementary capability to AI-DSS adoption (Liu et al., 2023; Truong, 2023). Organizations should implement knowledge management systems, cross-functional collaboration mechanisms, and continuous learning programs to enhance their capacity to acquire AI expertise, assimilate AI-generated insights, transform decision-making processes, and exploit AI capabilities for innovation. Innovation managers should also align AI-DSS adoption with innovation strategy, determining whether the focus is on exploitative innovation (improving existing offerings) or exploratory innovation (developing radical new offerings), as different strategic emphases may require different AI-DSS configurations and capabilities (Liu et al., 2023).

For technology leaders, the results emphasize the foundational importance of technology readiness, including robust IT infrastructure, high-quality data, and technical expertise (Ghaleb et al., 2021; Patil, 2021). Technology leaders should prioritize data governance initiatives, address legacy system constraints, invest in cloud computing and analytics infrastructure, and build technical talent pools. The negative effect of perceived complexity suggests the need for user-friendly interfaces, explainable AI algorithms, and comprehensive training programs to reduce cognitive barriers to adoption (Amini & Bakri, 2015). For policymakers, the findings underscore the influential role of regulatory support and ecosystem readiness in shaping adoption trajectories (Patil, 2021). Governments can accelerate AI-DSS diffusion by establishing clear regulatory frameworks that address liability, intellectual property, data privacy, and algorithmic accountability concerns. Financial incentives such as tax credits, grants, and subsidized training programs can reduce adoption barriers, particularly for small and medium-sized enterprises with limited resources. Policymakers should also promote industry-wide standards, best practices, and collaborative learning platforms to enhance ecosystem readiness (Dadhich et al., 2023).

6.3 Limitations and Future Research Directions

This study has several limitations that suggest avenues for future research. First, the cross-sectional design limits causal inference; longitudinal studies tracking organizations through adoption stages would provide stronger evidence of causal relationships and reveal temporal dynamics (Liu et al., 2023). Second, reliance on self-reported perceptual data introduces potential common method bias, despite statistical remedies. Future research could incorporate objective measures of technology adoption, innovation performance, and organizational capabilities to complement survey data (Patil, 2021).

Third, the quantitative approach, while enabling generalization and hypothesis testing, may not fully capture the nuanced organizational processes, contextual contingencies, and emergent phenomena associated with AI-DSS adoption. Mixed-methods designs combining surveys with in-depth case studies could provide richer insights into capability-building microfoundations, implementation challenges, and organizational learning processes (Truong, 2023). Configurational approaches such as fuzzy-set qualitative comparative analysis (fsQCA) could identify multiple equifinal pathways to successful AI-DSS adoption, recognizing that different combinations of factors may lead to similar outcomes in different contexts.

Fourth, the study focuses on TOE, DOI, and absorptive capacity perspectives; other theoretical lenses such as institutional theory, resource-based view, and social network theory could provide complementary insights. Future research could examine institutional pressures (coercive, mimetic, normative) shaping AI-DSS adoption, resource orchestration processes, and network effects in AI ecosystems (Smit et al., 2023). Fifth, individual-level factors including user acceptance, trust, resistance to change, and human-AI collaboration dynamics warrant deeper investigation. Multi-level models spanning individual, team, organizational, and ecosystem levels could provide more comprehensive understanding (Prijadi & Balqiah, 2023).

Sixth, the study does not fully address AI-specific considerations such as algorithmic explainability, bias and fairness concerns, ethical implications, and governance mechanisms. As these issues gain prominence in AI discourse, future research should explicitly incorporate them into adoption frameworks. Seventh, contextual factors including industry characteristics, organizational size, geographic location, and cultural dimensions may moderate the relationships identified in this study. Comparative studies across industries, countries, and organizational types would enhance understanding of contextual contingencies (Patil, 2021).

Finally, the study focuses on adoption decisions and immediate innovation outcomes; longer-term consequences including sustained innovation performance, organizational transformation, competitive advantage, and unintended effects deserve investigation. Longitudinal research tracking organizations over multiple years could reveal how AI-DSS adoption evolves over time and its cumulative effects on organizational capabilities and performance (Liu et al., 2023)

7. CONCLUSION

This research develops and proposes a comprehensive theoretical framework integrating TOE, DOI, and absorptive capacity perspectives to explain AI-DSS adoption dynamics in organizational innovation management contexts. By examining how technological, organizational, and environmental factors influence adoption through dual mediating pathways—organizational readiness and absorptive capacity and subsequently enhance innovation performance, we provide a nuanced understanding of this complex phenomenon (Ghaleb et al., 2021; Smit et al., 2023; Liu et al., 2023; Prijadi & Balqiah, 2023).

The proposed framework advances theory by integrating multiple theoretical lenses, unpacking mediating mechanisms, extending absorptive capacity theory to AI contexts, and linking adoption to innovation outcomes. Practically, it offers theory-grounded guidance for organizational leaders, innovation managers, technology professionals, and policymakers seeking to facilitate successful AI-DSS implementation. The findings underscore that AI-DSS adoption is not merely a technological decision but a multi-faceted organizational transformation requiring technological readiness, leadership commitment, cultural foundations, capability development, and supportive environmental conditions (Truong, 2023; Patil, 2021). As organizations navigate the complexities of the Fourth Industrial Revolution, AI-DSS represent powerful tools for enhancing decision-making quality, accelerating innovation processes, and achieving competitive advantage. However, realizing these benefits requires holistic approaches that simultaneously address technological, organizational, and environmental dimensions while building the readiness and absorptive capacity necessary to internalize and exploit AI capabilities effectively (Ghaleb et al., 2021; Liu et al., 2023). By providing a comprehensive framework for understanding key relationships, this research contributes to both scholarly understanding and practical implementation of AI-DSS in organizational innovation management.

Future research should build on this foundation through longitudinal designs, mixed-methods approaches, and attention to AI-specific considerations including explainability, ethics, and governance. Empirical testing of the proposed framework across diverse organizational contexts will validate and refine the relationships specified here. Ultimately, successful AI-DSS adoption depends on organizations' abilities to develop dynamic capabilities that enable continuous learning and adaptation in complex business environments (Prijadi & Balqiah, 2023; Liu et al., 2023).

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