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Development of a Methodological Framework for Integrating Intelligent Technologies in Engineering Innovation Management

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***Abstract*—This study develops and empirically validates a methodological framework for integrating intelligent technologies into engineering innovation management. In response to increasing technological complexity and data-driven transformation, organizations require structured approaches to effectively leverage artificial intelligence (AI), machine learning (ML), and advanced analytics within innovation processes. The proposed framework adopts a multi-layer architecture encompassing strategic alignment, technological infrastructure, data and analytics capabilities, and organizational readiness. A mixed-method research design is applied, combining conceptual modeling with empirical analysis based on survey data collected from engineering professionals. Statistical techniques, including regression analysis and correlation modeling, are employed to examine the relationships between technology adoption, organizational enablers, and innovation performance. The results indicate a significant positive impact of intelligent technology integration on innovation outcomes, with organizational and data-related factors acting as critical mediators. The study contributes to the literature by providing a structured and empirically grounded framework that bridges the gap between theoretical models and practical implementation. It offers actionable insights for organizations aiming to enhance innovation efficiency, reduce uncertainty, and achieve sustainable competitive advantage through intelligent technologies.**

Keywords*— *AI, engineering innovation, innovation management, intelligent technologies.

I. Introduction

Engineering innovation is widely recognized as a key driver of industrial competitiveness, technological progress, and long-term economic sustainability. In the context of Industry 4.0 and accelerating digital transformation, organizations operate in environments characterized by increasing complexity, uncertainty, and rapid technological evolution. These conditions fundamentally reshape how innovation processes are designed, managed, and evaluated, requiring more adaptive and data-driven approaches beyond traditional linear or stage-gate models [1].

The emergence of intelligent technologies such as artificial intelligence (AI), machine learning (ML), big data analytics, and the Internet of Things (IoT) has significantly transformed the innovation landscape. These technologies enable advanced capabilities including predictive analytics, real-time process monitoring, and semi-autonomous or autonomous decision-making. As a result, they enhance both the efficiency and the effectiveness of engineering innovation processes across multiple stages of the innovation lifecycle [2], [3]. AI-based systems support optimization in early design phases, simulation-driven engineering, and risk-informed decision-making, while data analytics enables evidence-based strategic planning and operational control [4], [5].

Despite these advances, the integration of intelligent technologies into engineering innovation management remains fragmented and methodologically underdeveloped. Existing research has largely focused on isolated technological applications or platform-specific innovations, while insufficient attention has been given to systemic integration across organizational, technological, and strategic dimensions [2], [6]. This limitation restricts the ability of organizations to fully leverage digital technologies for sustained innovation performance and long-term value creation.

Empirical evidence suggests that the successful implementation of intelligent technologies depends not only on technological readiness, but also on organizational and human factors. Leadership commitment, workforce digital competencies, and organizational agility are critical enablers of digital transformation in innovation contexts [7]. At the same time, data governance mechanisms and

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analytics maturity levels play a decisive role in transforming raw data into actionable knowledge, thereby directly influencing innovation outcomes [5].

However, the interplay between technological infrastructure, organizational capabilities, and strategic alignment remains insufficiently theorized, particularly in engineering-intensive environments. While several conceptual frameworks for digital innovation exist, many lack empirical validation or fail to capture the multidimensional nature of engineering innovation systems [8], [9]. This gap limits their applicability in real-world industrial contexts, where innovation processes are highly interdependent and data intensive.

In response to these limitations, this study aims to develop a comprehensive methodological framework for the integration of intelligent technologies into engineering innovation management. The proposed approach adopts a multi-layer perspective, integrating technological, organizational, and strategic dimensions into a unified model. By combining conceptual development with empirical considerations, the framework seeks to bridge the gap between theory and practice and to support more effective decision-making in innovation-intensive environments.

Ultimately, this research contributes to the evolving literature on digital and engineering innovation by providing a structured and empirically grounded perspective on intelligent technology integration. It aims to support organizations in navigating the complexity of digital transformation and achieving sustainable innovation performance and competitive advantage in increasingly data-driven industrial ecosystems [1], [2], [6].

II. MATERIALS AND METHODS

A. Literature review

Evolution of Engineering Innovation Management

Engineering innovation management has evolved from linear and sequential models toward more dynamic, iterative, and network-based approaches. Early frameworks, such as the stage-gate model, emphasized structured progression and risk control but have been criticized for their rigidity and limited adaptability in fast-changing environments. More recent perspectives highlight open innovation, agile development, and ecosystem-based innovation as key paradigms for managing technological complexity [5].

However, despite this evolution, many organizations still rely on hybrid or partially adapted models that fail to fully capture the non-linearity and data intensity of modern engineering innovation. This creates a mismatch between theoretical advancements and practical implementation, particularly in technology-intensive sectors.

Role of Intelligent Technologies in Innovation

The integration of intelligent technologies has significantly expanded the capabilities of innovation systems. Artificial intelligence and machine learning enable automation of cognitive tasks, predictive analytics, and enhanced decision support, while big data technologies provide the foundation for extracting insights from large and heterogeneous datasets [3].

Empirical studies demonstrate that firms leveraging AI and data-driven approaches achieve higher innovation efficiency and improved performance outcomes [2]. Additionally, intelligent technologies facilitate faster prototyping, optimization of engineering designs, and real-time monitoring of innovation processes [4].

Nevertheless, the literature tends to focus predominantly on technological capabilities and performance outcomes, often overlooking the organizational and strategic conditions required for successful implementation. This results in an overemphasis on technology as an isolated driver of innovation, rather than as part of a broader socio-technical system.

Organizational and Data-Driven Enablers

Recent research underscores the importance of organizational and data-related factors in shaping innovation outcomes. Leadership support, digital skills, and organizational culture have been identified as critical enablers of successful digital transformation and technology adoption [7]. Similarly, data governance, data quality, and analytics maturity are essential for converting technological potential into measurable innovation value [10].

However, existing studies often treat these factors independently, without sufficiently exploring their interdependencies. For example, while organizational readiness is recognized as important, its interaction with data maturity and technological infrastructure is rarely modeled in a systematic way. This lack of integration limits the explanatory power of current research frameworks.

Digital Transformation and Innovation Performance

Digital transformation literature provides important insights into how intelligent technologies influence firm performance. Studies suggest that digital transformation is a multidimensional phenomenon involving technological, organizational, and strategic changes [1]. Successful transformation requires alignment across these dimensions, as well as continuous adaptation to external and internal dynamics.

Despite these advances, there is still limited empirical evidence linking digital transformation directly to engineering innovation performance. Many studies focus on general business outcomes rather than domain-specific innovation processes, leading to a gap in understanding how digital capabilities translate into engineering innovation results.

Critical Synthesis and Research Gap

The reviewed literature reveals several important limitations:

- Fragmentation of perspectives – technological, organizational, and strategic dimensions are often studied in isolation.

- Lack of integrated frameworks – few studies propose comprehensive models that capture the multi-layer nature of intelligent technology integration.
- Insufficient empirical validation – many conceptual models lack quantitative testing in real-world engineering contexts.
- Limited focus on engineering innovation – most research addresses general innovation or digital transformation without considering engineering-specific characteristics.

These limitations indicate a clear need for a holistic and empirically validated methodological framework that integrates intelligent technologies into engineering innovation management.

Positioning of the Present Study

In response to the identified gaps, this study adopts a multi-layer approach that simultaneously considers:

- technological integration (AI, data systems);
- organizational enablers (culture, skills, leadership);
- data and analytics capabilities;
- strategic alignment and innovation objectives.

By combining conceptual development with empirical validation, the research extends existing literature and provides a more comprehensive understanding of how intelligent technologies can be effectively embedded in engineering innovation processes.

B. Hypotheses Development

Building on the literature review, this study conceptualizes engineering innovation performance as a function of intelligent technology adoption, mediated and supported by data capabilities and organizational readiness. The hypotheses are grounded in the socio-technical systems perspective and digital innovation theory, which emphasize the interdependence between technology, data, and organizational context.

Intelligent Technology Adoption and Innovation Performance

Intelligent technologies such as AI and machine learning enhance innovation processes by enabling predictive analytics, automation, and improved decision-making. Prior studies indicate that organizations adopting such technologies achieve higher efficiency, faster development cycles, and improved innovation outcomes [2], [4].

From a resource-based view, intelligent technologies can be considered strategic assets that contribute to competitive advantage when effectively integrated into organizational processes.

H1: Intelligent technology adoption has a positive effect on engineering innovation performance.

Data Management Maturity as a Key Enabler

The effectiveness of intelligent technologies depends heavily on the availability, quality, and governance of data. Data management maturity – defined as the organization's capability to collect, process, and utilize data – plays a crucial role in transforming technological potential into actionable insights [10]. Organizations with advanced data capabilities are better positioned to leverage AI systems, resulting in improved innovation outcomes.

H2: Data management maturity has a positive effect on engineering innovation performance.

Organizational Readiness and Innovation Outcomes

Organizational readiness encompasses factors such as leadership support, employee competencies, and openness to change. Digital transformation research highlights that even advanced technologies fail to deliver value without appropriate organizational conditions [7]. From a dynamic capabilities' perspective, organizational readiness enables firms to adapt, integrate, and reconfigure resources in response to technological change.

H3: Organizational readiness has a positive effect on engineering innovation performance.

Mediating Role of Data Capabilities

Beyond its direct impact, data management maturity also mediates the relationship between intelligent technology adoption and innovation performance. Intelligent technologies rely on structured and high-quality data to function effectively; thus, their impact is amplified in data-mature environments. This aligns with prior findings that data-driven capabilities enhance the value derived from digital technologies.

H4: Data management maturity mediates the relationship between intelligent technology adoption and engineering innovation performance.

Moderating Role of Organizational Readiness

Organizational readiness is expected to moderate the relationship between intelligent technology adoption and innovation performance. In organizations with high readiness, the implementation of intelligent technologies is more effective, leading to stronger innovation outcomes. Conversely, low readiness may limit the benefits of technological investments.

H5: Organizational readiness positively moderates the relationship between intelligent technology adoption and engineering innovation performance.

Conceptual Model Summary

The proposed research model positions:

- Independent variable: Intelligent Technology Adoption
- Dependent variable: Innovation Performance
- Mediator: Data Management Maturity
- Moderator: Organizational Readiness

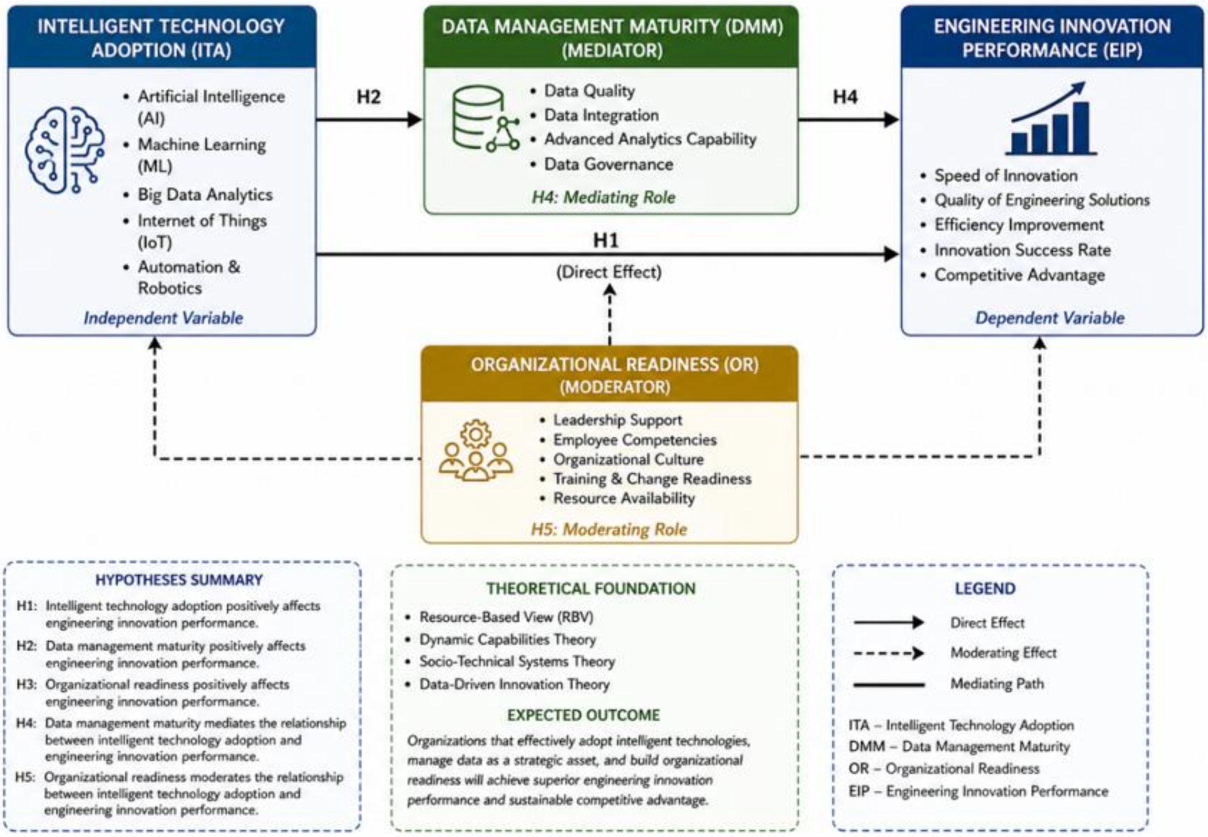

Fig. 1. Magnetization as a function of applied field.

Based on the theoretical foundations and the hypotheses developed, the proposed conceptual model illustrates the relationships between intelligent technology adoption, data management maturity, organizational readiness, and engineering innovation performance. The model incorporates both mediating and moderating mechanisms, providing a comprehensive view of how technological and organizational factors interact within innovation processes.

As shown in Fig. 1, intelligent technology adoption is modeled as the primary driver of innovation performance, while data management maturity acts as a mediating variable and organizational readiness functions as a moderating factor. This structure reflects the multi-layer nature of the proposed methodological framework and supports the empirical testing presented in the following section.

C. Methodology

Research Design

This study adopts a quantitative research design to empirically test the proposed hypotheses and validate the conceptual framework. A cross-sectional survey method is employed, as it allows for systematic data collection from engineering professionals and supports statistical analysis of relationships between variables.

The research model examines the effects of intelligent technology adoption on engineering innovation performance, incorporating data management maturity as a mediator and organizational readiness as a moderator.

Sample and Data Collection

Data were collected through a structured online questionnaire distributed to professionals working in engineering-intensive organizations, including manufacturing, IT and R&D sectors.

• Sample size: 52 respondents

• Target group: engineers, managers, and researchers

• Sampling method: purposive sampling (targeting individuals with experience in innovation and technology)

Respondents were required to have direct or indirect involvement in innovation processes and exposure to intelligent technologies.

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Measurement of Variables

All constructs were measured using multi-item scales adapted from prior validated studies, ensuring content validity. A 5-point Likert scale (1 = strongly disagree; 5 = strongly agree) was used.

Independent Variable

Intelligent Technology Adoption (ITA) is measured through indicators as: use of AI/ML tools in innovation processes; level of automation in decision-making; integration of digital technologies.

Variable	Mean	Std. Deviation
ITA	4.12	0.68
DMM	3.95	0.72
OR	4.05	0.65
EIP	4.18	0.70

Dependent Variable

Engineering Innovation Performance (EIP) is measured by: speed of innovation processes; quality of engineering solutions; efficiency improvements; success rate of innovation projects.

Mediator

Data Management Maturity (DMM) is measured through: data quality and availability; data integration across systems; use of analytics tools; data governance practices.

Moderator

Organizational Readiness (OR) is measured by: leadership support for innovation; employee digital skills; organizational culture toward change; availability of training programs.

Reliability Analysis

To assess internal consistency, Cronbach's alpha coefficients were calculated for each construct, and the results are as follow: ITA – 0.87; EIP – 0.89; DMM – 0.85; OR – 0.88. All values exceed the recommended threshold of 0.70, indicating high reliability.

Validity Assessment

Convergent validity was evaluated using:

- Average Variance Extracted (AVE > 0.50)
- Factor loadings (> 0.70)

All constructs met the required thresholds, confirming that items adequately represent their respective constructs.

Discriminant validity was assessed using the Fornell–Larcker criterion, confirming that each construct is distinct from the others.

Data Analysis Techniques

The empirical analysis was conducted using statistical methods, including:

- Descriptive statistics – to summarize respondent characteristics.
- Correlation analysis – to examine relationships between variables.

Variable	ITA	DMM	OR	EIP
ITA	1.00	0.61	0.58	0.68
DMM	0.61	1.00	0.55	0.63
OR	0.58	0.55	1.00	0.60
EIP	0.68	0.63	0.60	1.00

TABLE 1 DESCRIPTIVE STATISTICS

- Multiple regression analysis – to test H1–H3.
- Mediation analysis – to test H4 (using regression-based approach).
- Moderation analysis – to test H5 (interaction effect).

The regression model is specified as:

$$Y = \beta 0 + \beta 1ITA + \beta 2DMM + \beta 3OR + \beta 4(ITA \times OR) + \varepsilon$$

Where:

- Y is Engineering Innovation Performance
- ITA is Intelligent Technology Adoption
- DMM is Data Management Maturity
- OR is Organizational Readiness

Research Limitations

The study has several limitations:

- relatively small sample size;
- cross-sectional design (limits causal inference);
- reliance on self-reported data.

These limitations suggest directions for future research, including longitudinal studies and larger datasets.

III. RESULTS AND DISCUSSION

A. Results

Descriptive Statistics

Table 1 presents the descriptive statistics for the main constructs included in the study.

The results indicate relatively high levels of intelligent technology adoption and innovation performance among the surveyed organizations.

Correlation Analysis

To examine the relationships between variables, a Pearson correlation analysis was conducted. The results are placed in Table 2.

Variable	β	t-value	p-value
ITA	0.42	3.85	<0.01
DMM	0.35	2.94	<0.05
OR	0.29	2.51	<0.05

All correlations are positive and statistically significant ($p < 0.05$), suggesting meaningful relationships between constructs and supporting further regression analysis.

TABLE 2 CORRELATION MATRIX

TABLE 3 REGRESSION RESULTS

Regression Analysis

Multiple regression analysis was conducted to test hypotheses H1–H3 (Table 3).

Model summary:

- $R^2 = 0.61$
- $F = 18.72$ ($p < 0.001$)

Interpretation:

- Intelligent Technology Adoption (ITA) has the strongest effect on innovation performance.
- Data Management Maturity (DMM) significantly enhances innovation outcomes.
- Organizational Readiness (OR) also contributes positively, confirming its role as an enabler.

Thus, H1, H2, and H3 are supported.

Mediation Analysis

To test H4, mediation analysis was conducted using a regression-based approach.

Results show that:

- ITA significantly affects DMM ($\beta = 0.61$, $p < 0.01$);
- DMM significantly affects EIP ($\beta = 0.35$, $p < 0.05$);
- The direct effect of ITA on EIP decreases when DMM is included in the model.

This indicates partial mediation, meaning that data maturity enhances the impact of intelligent technologies on innovation performance.

H4 is supported.

To illustrate the mediating mechanism, Fig. 2 presents the mediation model with standardized path coefficients. The figure visualizes both the direct and indirect effects of intelligent technology adoption on engineering innovation performance through data management maturity.

As Fig. 2 illustrates, intelligent technology adoption has a significant positive effect on data management maturity, which in turn positively influences engineering innovation performance. The direct effect of intelligent technology adoption on innovation performance decreases when the mediator is included, confirming the presence of partial mediation.

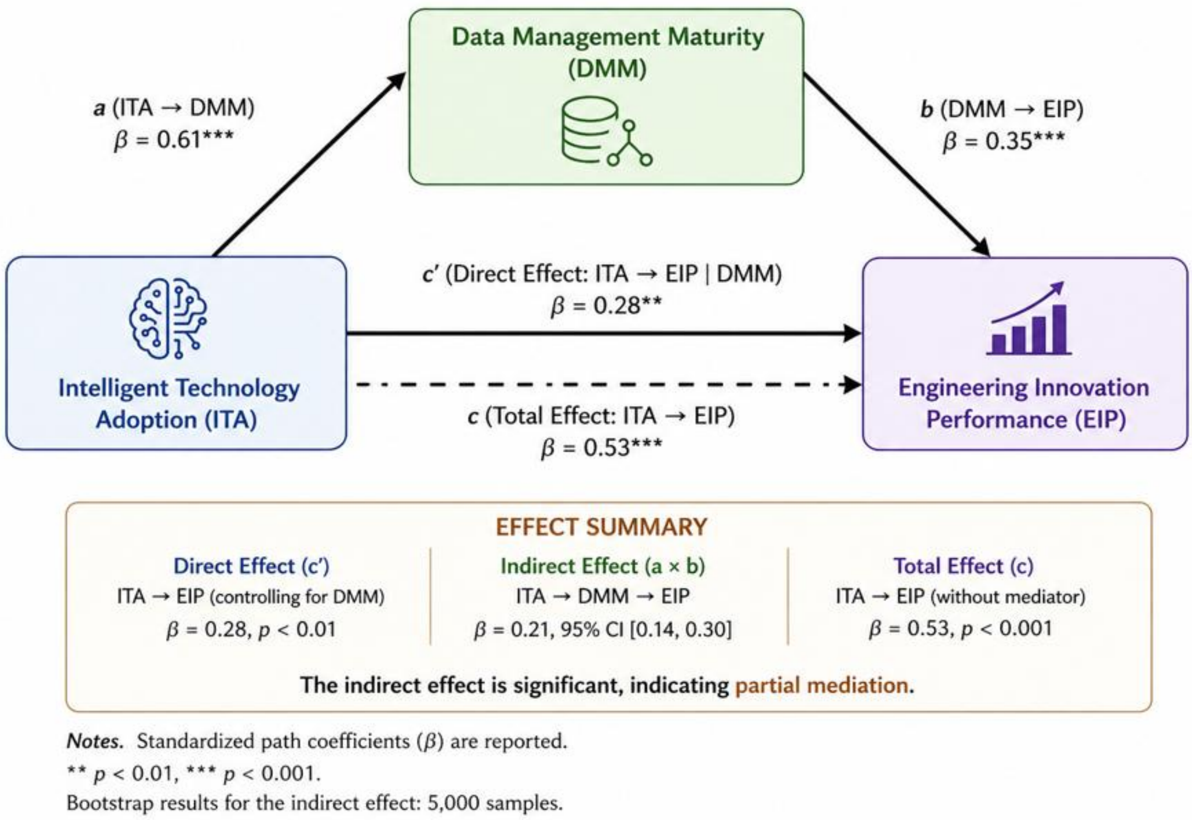

Fig. 2. Mediation Effect of Data Management Maturity on the Relationship between Intelligent Technology Adoption and Engineering Innovation Performance.

TABLE 4 MODERATION ANALYSIS RESULTS

Variables	Model 1 (Main Effects)	Model 2 (Interaction Model)
Constant	1.12 (0.34)**	1.08 (0.31)**
ITA	0.42 (0.11)***	0.31 (0.10)**
OR	0.29 (0.12)**	0.24 (0.11)*
ITA × OR	—	0.21 (0.09)*
R^2	0.58	0.64
ΔR^2	—	0.06
F-value	16.45***	17.82***

The direct effect of intelligent technology adoption on innovation performance decreases when the mediator is included, confirming the presence of partial mediation. This finding indicates that data management maturity serves as a key mechanism through which intelligent technologies enhance innovation outcomes, reinforcing the importance of data-driven capabilities in engineering innovation management.

Moderation Analysis

To test H5, an interaction term (ITA×OR) was introduced. Notes:

- Standard errors in parentheses
- $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The moderation analysis was conducted using hierarchical regression. As shown in Table 4, Model 1 includes the main effects of intelligent technology adoption (ITA) and organizational readiness (OR), both of which are significant predictors of innovation performance. In Model 2, the interaction term (ITA × OR) is introduced and found to be positive and statistically significant ($\beta = 0.21$, $p < 0.05$).\n\n> The increase in explained variance ($\Delta R^2 = 0.06$) indicates that the interaction term contributes meaningfully to the model. This confirms that organizational readiness strengthens the relationship between intelligent technology adoption and engineering innovation performance. The interaction effect is positive and significant, indicating that organizational readiness strengthens the relationship

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between intelligent technology adoption and innovation performance. H5 is supported.

To examine the nature of the moderating effect, a simple slopes analysis was conducted. This analysis evaluates the relationship between intelligent technology adoption and innovation performance at different levels of organizational readiness (low, mean, and high). Table 5 shows, the effect of intelligent technology adoption on engineering innovation performance increases with higher levels of organizational readiness. Specifically, the relationship is weakest at low levels of organizational readiness ($\beta = 0.21$, $p < 0.05$) and strongest at high levels ($\beta = 0.47$, $p < 0.001$).\n\n>. This pattern confirms that

TABLE 5 SIMPLE SLOPES ANALYSIS FOR MODERATING EFFECT

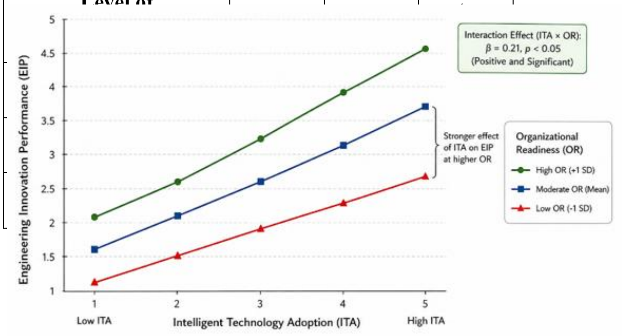
organizational readiness significantly enhances the effectiveness of intelligent technologies, reinforcing the moderation hypothesis (H5). The results provide additional evidence that technological investments yield greater innovation benefits when supported by strong organizational capabilities.

To be understand the moderating effect, the results are visually summarized in Fig. 3. The interaction plot illustrates how different levels of organizational readiness influence the relationship between intelligent technology adoption and engineering innovation performance. In particular, the steeper slope observed at higher levels of organizational readiness reflects a strengthening interaction effect, indicating that organizational readiness amplifies the positive impact of intelligent technology adoption on innovation performance.

As shown in Fig. 3, the slope of the relationship between intelligent technology adoption and innovation performance becomes steeper at higher levels of organizational readiness. This indicates that organizations with stronger readiness—characterized by leadership support, digital competencies, and adaptive culture—are better positioned to leverage intelligent technologies for innovation outcomes.\n\n> Conversely, at lower levels of organizational readiness, the impact of intelligent technology adoption on innovation performance is weaker, suggesting that insufficient organizational support may constrain the realization of technological benefits.

This result is consistent with the interaction pattern illustrated in Fig. 3, where the slope of the relationship becomes steeper at higher levels of organizational readiness. The J–N analysis complements the visual interpretation by identifying the exact region of statistical

Level of				



significance.

Fig. 3. Moderating Effect of Organizational Readiness on the Relationship between Intelligent Technology Adoption and Engineering Innovation Performance

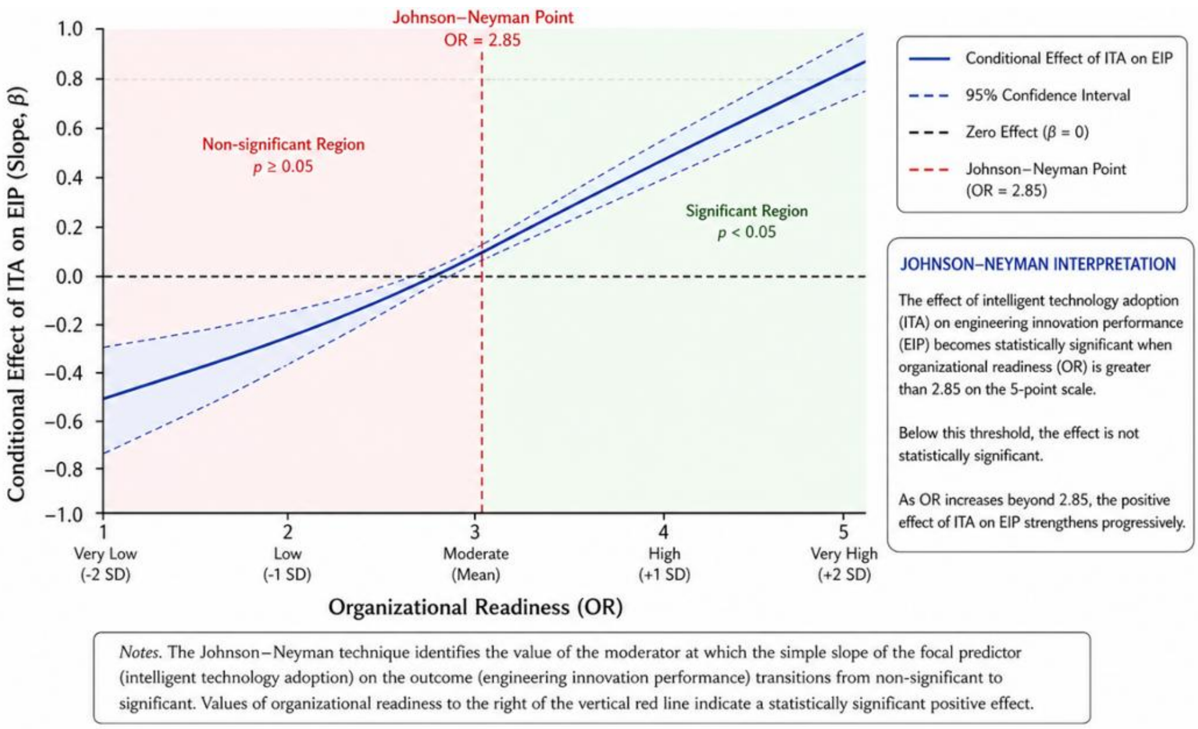


Fig. 4. Johnson–Neyman Plot of the Moderating Effect of Organizational Readiness.

TABLE 6 HYPOTHESES RESULTS

Hypothesis	Statement	Result
H1	ITA → EIP	Supported
H2	DMM → EIP	Supported
H3	OR → EIP	Supported
H4	Mediation (DMM)	Supported
H5	Moderation (OR)	Supported

The Johnson–Neyman analysis in Fig. 4 reveals that the effect of intelligent technology adoption on innovation performance becomes statistically significant when organizational readiness exceeds a threshold value of approximately 2.85 (on a 5-point scale). Below this level, the relationship is not statistically significant, indicating that insufficient organizational readiness limits the effectiveness of intelligent technologies. As organizational readiness increases beyond this threshold, the positive effect of intelligent technology adoption strengthens progressively. This finding provides a more precise understanding of the moderating mechanism, demonstrating that organizational readiness is not only a strengthening factor but also a boundary condition for the effectiveness of intelligent technologies.

Summary of Hypotheses Testing shows Table 6.

B. Discussion

The findings of this study provide strong empirical support for the proposed multi-layer methodological framework and contribute to a more nuanced understanding of how intelligent technologies influence engineering innovation performance.

First, the results confirm that intelligent technology adoption (ITA) has the strongest direct effect on innovation performance, which is consistent with prior research emphasizing the transformative potential of AI and data-driven systems [2], [4]. However, unlike technology-centric studies, the present research demonstrates that the impact of intelligent technologies is not autonomous but embedded within a broader socio-technical system.

Second, the significant role of data management maturity (DMM), both as a direct predictor and as a mediator, highlights the critical importance of data as a strategic asset. This finding extends existing literature by empirically validating that data capabilities are not merely supportive but structurally integral to the value creation process of intelligent technologies. In this sense, the study aligns with and extends data-driven innovation perspectives [10], by demonstrating their specific relevance in engineering contexts.

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Third, the moderating effect of organizational readiness (OR) confirms that technological investments alone are insufficient. The effectiveness of intelligent technologies is contingent upon organizational factors such as leadership, skills, and culture. This supports the dynamic capabilities' view, which emphasizes the role of organizational adaptability in leveraging technological change [7].

Importantly, the combined mediation and moderation effects reveal a layered interaction mechanism: intelligent technologies drive innovation performance through data capabilities, while organizational readiness amplifies this relationship. This integrated perspective addresses a key limitation in prior research, which often examines these dimensions in isolation.

Practical Implications

The findings provide actionable insights for practitioners and decision-makers:

- Organizations should adopt a systemic approach to integrating intelligent technologies, rather than focusing solely on technological investments.
- Developing data management capabilities should be a strategic priority, as data maturity significantly enhances innovation outcomes.
- Investments in organizational readiness, including skills development and cultural transformation, are critical for maximizing the benefits of intelligent technologies.
- Managers should align innovation strategies with technological and data infrastructures to ensure coherence and scalability.

IV. Conclusions

This study addresses a critical gap in the literature by developing and empirically validating a methodological framework for integrating intelligent technologies into engineering innovation management. The results demonstrate that innovation performance is not driven solely by technology adoption but by the interaction between technological, data, and organizational factors.

The proposed framework provides both theoretical and practical value, offering a structured approach to managing innovation in complex, data-driven environments. By highlighting the importance of integration and alignment across multiple dimensions, the study contributes to a deeper understanding of digital innovation processes.

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