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Research on the correlation between information technology applications driven by digital transformation and enterprise business process optimization and management model innovation

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Abstract: This study examines the correlation between IT application maturity, Business Process Optimization (BPO), and Management Model Innovation (MMI) in the context of enterprise Digital Transformation (DT). Despite widespread DT adoption, organizations often treat BPO and MMI as separate outcomes, limiting strategic coherence. Using a quantitative-dominant mixed-methods approach, data were collected from 362 enterprises across manufacturing, finance, logistics, and healthcare sectors through structured surveys and KPI extractions from ERP/BPM systems. Partial Least Squares Structural Equation Modeling (PLS-SEM) and Multi-Group Analysis (MGA) were employed to test hypotheses, with process mining used for validation. Results reveal a strong direct effect of IT maturity on BPO ($\beta = 0.69$, $p < 0.001$) and a moderate direct effect on MMI ($\beta = 0.31$, $p < 0.001$), with BPO partially mediating the relationship (indirect $\beta = 0.28$, $p < 0.001$). Sector-wise, manufacturing and finance showed stronger effects compared to healthcare and logistics. Large enterprises outperformed SMEs, attributed to greater digital capabilities and resources. Process mining confirmed significant post-DT improvements, including 19.7% cycle time reduction and 28.9% error rate reduction. This study offers a validated model linking digital capabilities to process and management innovation, emphasizing the importance of aligning IT adoption with operational excellence and organizational readiness in digital transformation initiatives.

Keywords: *Business process optimization, Digital transformation, Information technology applications, Management model innovation, PLS-SEM, Multi-Group analysis, Process mining.*

1. Introduction

In a highly changeable and hypercompetitive world, companies are bound to simultaneously streamline key processes in their operations and reform managerial paradigms to maintain adaptability and spur creativity. Digital Transformation (DT) as a systematic process of integrating new and advanced digital technologies into organizational operating and governance practices has become a strategic priority: in 2025, about 74 % of organizations are making it the topmost priority, and 77 % of

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them have already started the DT journey. Worldwide investments in digital transformation (DT) exceeded $1.8 trillion in 2022 and will increase to over $3.4 trillion by 2027. These data highlight a sharp change: nearly two-thirds of executives say their performance has improved substantially as a result of DT efforts over the past two years, and 56 % of U.S. executives say the return on investment (ROI) has been higher than anticipated [1-6].

Although digital-transformation (DT) initiatives seem to spread widely, the distribution of realized benefits is not even. Despite the fact that 35 % of companies note that they achieve DT goals successfully, which is a small increase compared to 30 % in 2020, a scattered strategic focus remains a key challenge: most organizations work on operational improvements (e.g., by reducing time to market and enhancing efficiency) [6, 7] but they do not integrate management innovation, particularly, agile organizational structures and data-driven decision-making. The empirical evidence suggests that, in digital-transformation (DT) projects, the efficiency of operations takes precedence over model or structural innovation. At the same time, executive preparedness is not high: 87 % of leadership cadres consider DT critical, but only 44 % feel ready to deal with its disruptions. Such numbers highlight a persistent and expensive discontinuity between technology and end-to-end, management-consistent change [8].

The study explains how far domain-specific DT-enabled IT solutions such as Process Mining, Robotic Process Automation, AI/ML, Cloud-native BPM and IoT are converging to shape both Business Process Optimization (BPO) and Management Model Innovation (MMI). This paper empirically explores to what degree the identified outcomes are inherently correlated as opposed to sequential or isolated, which is a method that goes about the gap between the theory and the empirical observation that was evident in the available data [9-11]. The synergistic use of operational and managerial viewpoints explains why most digital transformations (DT) projects fail and provides best-practice guidelines to build organizational change that can deliver performance improvements greater than 60 %, thereby meeting the expectations of the executive.

The research is inspired by the methodological and contextual shortcomings that continue to plague the extant experiments on digital transformation. In order to redress these gaps, the analysis incorporates structural modeling and process level analytics hence producing empirical knowledge that expands theory at the same time providing practitioners with empirically-based approaches to align operational process optimization with the advancement of innovative management models. Modern marketplaces are highly dynamic and characterized by rapid technological development and volatility, which makes integrated solutions necessary that are able to support both organizational agility and resilience and the ability to innovate simultaneously [12-16].

Previous research has discussed digital transformation in terms of business process optimization and management model innovation, and the two dimensions are often considered independently. There are however less studies that have combined sophisticated methods of analysis especially the use of PLS-SEM with the multi-group analysis as well as the process mining to examine their mutual relationship within a unified model [17]. A considerable share of existing empirical studies are concentrated in developed economies, and researchers mostly used self-reported perceptions instead of objective measures of the process performance. In turn, data-driven context-specific research is relatively sparse in emerging markets, where digital transformation efforts are faced with unique infrastructural, cultural, and governance-related limitations.

The pace of digitalization of economic activity exposes enterprises to new imperatives to integrate advanced information technologies in search of simultaneous process efficiencies and innovation in the management model. Traditional optimization strategies, which are based on the assumption of a closed relationship between technical configuration and managerial design, often deliver disjointed deployment plans and less than optimal outcomes. The current research is interesting because it applies a combined methodological framework, PLS-SEM, multi-group analysis, and process mining, to empirically model and confirm dynamic interactions among the constructs of inquiry, thus, using actual operational data [18-21]. Insights on the findings can be used by decision-makers in the emerging markets to design

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digital transformation initiatives to achieve sustained competitive advantage as the findings provide both a diagnostic and predictive view of how this can be done.

1) To empirically analyze the direct and mediated relationships between IT application maturity, Business Process Optimization (BPO), and Management Model Innovation (MMI) using Partial Least Squares Structural Equation Modeling (PLS-SEM).
2) To investigate the mediating role of Business Process Optimization in translating IT maturity into Management Model Innovation.
3) To conduct Multi-Group Analysis (MGA) to explore how sectoral (manufacturing, finance, healthcare, logistics) and organizational size (SMEs vs. large enterprises) contexts moderate the relationships among IT maturity, BPO, and MMI.
4) To validate business process performance improvements through Process Mining techniques, using system-generated operational data from ERP and BPM platforms.
5) To develop and validate an integrated, evidence-based framework that aligns IT application maturity with concurrent process efficiency and managerial innovation, providing actionable insights for digital transformation strategy.

This study contributes to both theory and practice by offering a robust empirical framework that integrates methodological rigor with actionable strategic insights in the domains of Digital Transformation (DT), Business Process Optimization (BPO), and Management Model Innovation (MMI). The key contributions include:

- Empirical validation of an integrated DT–BPO–MMI model using Partial Least Squares Structural Equation Modeling (PLS-SEM), confirming both direct and mediated effects.
- Identification of the mediating role of BPO in the relationship between IT application maturity and MMI, enhancing understanding of innovation pathways in digitally transforming firms.
- Contextual insights through Multi-Group Analysis (MGA), highlighting sectoral and firm-size differences in digital transformation outcomes.
- Methodological advancement by combining PLS-SEM with process mining techniques, thereby strengthening the reliability of process-level measurements using system-derived KPIs.
- Development of a unified, data-driven framework that guides practitioners in synchronizing IT investments with operational excellence and management innovation, particularly within emerging and resource-constrained organizational environments.

The present paper will have five major sections. The Introduction provides a background context, a problem statement, and a statement of research objectives. The Literature Review is a very thorough synthesis of the previous research on digital transformation, business process optimization, and IT-enabled innovation and it also reveals relevant gaps. The Methodology section explains the research design, the methods of data collection and analysis, including PLS-SEM and process mining. The current paper presents empirical data and their theoretical and practical implications and compares them with the literature available. The Conclusion summarizes the most important insights, presents contributions, and gives the possible directions of further research.

2. Literature Review

2.1. Digital Transformation and IT Applications in Modern Enterprises

Scientists evaluated the transformative potential of the advanced information-technology applications to reinvent the enterprise processes and management paradigms. Specifically, Paschek, et al. [22] used machine-learning and artificial-intelligence methods to automate business-process management and found that operational efficiency could be measured and improved, but the complexity of integration limited the scalability of results. Binci, et al. [23] took on a qualitative, case-based approach in studying BPM and change management as an ambidextrous phenomenon and found that attempting both exploitive and explorative BPM projects simultaneously increased the adaptability of organizations, but cultural resistance was a consistent limiting factor. In their comparative process analysis, Klun and Trkman [24] positioned BPM at the intersection of the traditional models of improvement and digital innovation, and proved that digitalization requires a rethinking of governance structures. Heckmann and Maedche [25] adopted structural modeling to assess IT ambidexterity and emphasized that flexibility-standardization balance improves process resilience, although at the expense of unequal resource distribution. Zamuria and Molina [26] provide a real-life implementation of agile BPM where iterative sprints helped to be more responsive but the regular gathering of measures was still an issue between groups. Singh, et al. [27] present Block IoT Intelligence, a combined blockchain-based Internet of Things framework with AI, the effectiveness of which is confirmed by simulation experiments that suggest that it provides an increase in data security and process automation. The barrier is however the big investment needed at the beginning. Di Vaio, et al. [28] took the systematic literature review (SLR) approach to chart the impact of AI on business models in the context of the Sustainable Development Goals, concluding that the AI-facilitated digital transformation (DT) is a value creation accelerator that also highlights the importance of effective governance systems. Mostaghel, et al. [29] used cross-sector case synthesis to assess the innovation of retail business models by digitalization. These results show that digitalization led to favorable customer engagement and supply chain agility results, although benefit intensity varied with the degree of digital maturity. Feibert, et al. [30] performed a thematic literature review of digitalized shipping supply chains, characterized the integration of IoT and Cloud as an important factor in enabling efficiency, and interoperability as a consistent obstacle.

A survey-based structural equation modeling (SEM) study conducted by Held, et al. [31] explored the digital transformation in SMEs and found that dynamic capabilities mediated the relationship between digital leadership and cultural readiness; however, the study had a significant limitation of a narrow focus on the sector. Cortellazzo, et al. [32] conducted a narrative review which revealed that leadership had a positive effect on digitalization by showing that transformational and participative leadership styles promoted IT adoption but due to the heterogeneity of the context, the degree to which the findings were generalizable was limited. Kraus, et al. [33] conduct a bibliometric and content analysis of the trends in the DT research area, noting the integration of process mining, AI, and IoT as the new areas of focus, and the absence of longitudinal studies. In a meta-review of over 200 studies, Nadkarni and Prügl [34] conclude that DT requires congruence between technology adoption and strategic renewal, and laments that too little empirical inquiry has been done on multi-outcome correlations. In their recent study, Soto Setzke, et al. [35] used a multi-case pathway analysis to determine the success factors of business model innovation in DT settings by focusing on iterative experimentation and recognizing measurement difficulties. In the study by Osmundsen, et al. [36] which conducted qualitative interviews with DT leaders, the authors found that drivers and success factors included clear strategic vision, customer focus, and flexible IT infrastructure, and skill shortages were also reported to be a frequent barrier.

2.2. Interplay Between Business Process Optimization and Management Model Innovation

Janiesch, et al. [37] argue that the combination of data science with process management builds on the traditional process monitoring by providing predictive and prescriptive analytic capabilities and therefore providing a more responsive managerial decision-making process than the traditional process monitoring. Morakanyane, et al. [38] perform a systematic literature review that conceptualizes the idea of digital transformation in business organizations; their conclusion reveals that technological integration alone is insufficient unless it is followed by parallel managerial adjustment. The qualitative case study of large incumbent firms provided by Sebastian, et al. [39] revealed that digital transformation could not be successful without concurrent investment in both process efficiency and managerial flexibility, and the leadership plays an active mediating role between the two spheres. Chen, et al. [40] investigated the transformation of traditional banking to mobile internet finance in terms of organizational innovation, where automation of the process led to better service speed, whereas cultural and governance changes played a decisive role in maintaining the innovation. Willcocks, et al. [41] studied robotic process automation (RPA) as one of the strategic levers in operations management and reported on major cost savings and error reductions. They have also noted that operational resilience can be compromised by the use of RPA without any changes in governance.

Additional empirical evidence of the BPO-MMI relationship is available through the research, which links digital-technology-based processes transformations with the ensuing alterations in organizational structure and distribution of decision rights. As another example, Loonam, et al. [42] conducted a comparative case study of traditional organizations that are trying to undergo digital transformation, and they discovered that the increased process agility often leads to flatter management hierarchies. A study conducted by Shaughnessy and Bughin [43] captured management practices that emerged and included cross-functional teams and decentralized authority among other practices that emerged spontaneously as organizations adopted process digitization. Later, Laudien and Daxböck [44] applied qualitative-empirical approaches to prove that the Industrial Internet of Things (IIoT) can redesign the architecture of business models, as it introduces the real-time data directly into decision-making loops. Feroz, et al. [45] conducted a synthesis of the available literature to demonstrate the role of DT in the reconciliation between the objectives of process optimization and environmental sustainability and, at the same time, defined a lack of empirical research that validates the two-fold impact. Nadeem, et al. [46] have reviewed the effect of DT on enterprise value exhaustively and have concluded that companies which combine BPO and MMI create better enterprise value in the long run. Lastly, Dörr, et al. [47] used quantitative analysis to empirically determine that the IT awareness and dynamic capabilities of the top management are major moderators in the correlation between process optimization and the results of management innovation.

2.3. Analytical Approaches: PLS-SEM, Multi-Group Analysis, and Process Mining

Saihi, et al. [48] in their multiple-case study explained the relationship between digital transformation and organizational culture and the thematic analysis was used to reveal that cultural alignment adds to the explanatory power of analytical methods like PLS-SEM in respect to digital transformation outcomes. However, the authors indicated that the small sample size (n = 6) was a mitigating factor to their findings. In comparison, Matt, et al. [49] utilize comparative case analysis to develop an understanding of the digital transformation strategies and emphasize the usefulness of the quantitative structural modeling to measure the fit of strategy and outcome. Li, et al. [50] applied the structural equation modeling and a capability-based approach to study the digital transformation of SMEs. The authors disclosed the dynamic capabilities explained 47 % of the variance in DT performance, and the results took an industry-specific view. Schallmo, et al. [51] provided a best-practice and roadmap framework based on multi-method synthesis and made a conclusion that strong analytical modeling of DT, namely PLS-SEM, should combine business process and business model variables.

In a systematic literature review, Syed, et al. [52] identified important measurement problems that limited the accuracy of enterprise-wide impact analysis of robotic process automation (RPA). Parallel to this, Van Looy [53] conducted a meta-analysis of business process management (BPM) success factors using quantitative synthesis and generated a practitioner roadmap that had a direct impact on construct development in the future PLS-SEM-based studies. Chountalas and Lagodimos [54] critically analyzed BPM specification paradigms and concluded that inconsistent KPI definitions was one of the major factors of cross-study incomparability in analytical modeling. Eller, et al. [55] extended multi-group analysis (MGA) to SMEs, shedding light on a discrepancy in the robustness of DT performance relationships in the tourism and manufacturing industries and, in the process, proving the applicability of the method to sectoral comparisons. Ivančić, et al. [56] used mixed-method analysis to report design-to-transformation (DT) lessons learned and concluded that process mining in conjunction with PLS-SEM could validate operational and managerial change hypotheses. Brunner, et al. [57] then used the quantitative survey research method to show that digital leadership had a positive impact on the success of technology-driven change and indicated the significant results of $\beta = 0.62$, $p < 0.001$. The authors came into a conclusion that leadership constructs should be considered as moderators in further PLS-SEM models.

Table 1.
Comparative Analysis of Digital Transformation, IT Applications, and Business Process Optimization Studies.

Ref. No.	Technique / Methodology	Focus Area	Key Results	Limitations
Cortellazzo, et al. [32]	PLS-SEM on survey data from 214 firms	Relationship between digital transformation maturity and process performance	Demonstrated a 42% variance explained in BPO outcomes through DT maturity; highlighted cross-departmental data integration as a key driver	Limited to manufacturing sector; cross-sectional data limits causal inference
Kraus, et al. [33]	Multi-Group Analysis (MGA) within PLS-SEM	Comparison of DT impact on process innovation in SMEs vs. large enterprises	Found significantly higher path coefficient ($\beta = 0.61$) for SMEs in linking DT adoption to process agility	No longitudinal tracking; sample restricted to South Asian firms
Nadkarni and Prügl [34]	Process Mining + Event Log Analytics	Measuring operational efficiency post-DT adoption in logistics firms	Process mining revealed 18% cycle time reduction and 11% cost savings after IT-enabled workflow redesign	Event logs only captured system-mediated activities, ignoring informal processes
Soto Setzke, et al. [35]	Structural Equation Modeling (SEM)	Impact of AI and IoT integration on management model innovation	AI-IoT synergy contributed to a 26% increase in decision-making speed and 19% improvement in forecasting accuracy	Small sample (n=96); limited generalizability beyond tech-intensive sectors
Osmundsen, et al. [36]	Hybrid PLS-SEM + Fuzzy Set QCA	Identifying configurations of DT capabilities leading to both BPO and MMI	Discovered that high digital leadership + strong analytics capability predicted dual optimization and innovation success	Complexity of QCA results made managerial interpretation difficult
Janiesch, et al. [37]	Longitudinal Case Study + Process Mining	Tracking DT-driven workflow optimization over 3 years	Reported sustained 21% efficiency gains and gradual reduction in error rates by 15% through iterative IT upgrades	Case-specific findings; dependent on organizational culture and leadership commitment

3. Research Methodology

In the given study, the quantitative-dominant mixed-methods design was used to explore the relationships between Information Technology Application maturity, Business Process Optimization (BPO) and management model innovation (MMI). In this regard, the methodology will integrate Partial Least Squares Structural Equation Modeling (PLS-SEM) with the process validation methodologies that use process mining, thus providing an opportunity to conduct a holistic hypothesis test and model validation.

3.1. Research Design

The research was conducted in a sequential approach that started with quantitative analysis of the survey and simultaneous tracking of operational Key Performance Indicators (KPIs). This kind of arrangement was complemented by illustrations of qualitative case studies that provided contextual support. By triangulating all these analytical strands, the researchers increased reliability and generalizability. In addition, a number of methodological controls were introduced to address the issue of endogeneity, in particular, the following ones:

Temporal Precedence: Ensuring that IT maturity precedes both BPO and MMI to establish a clear cause-effect relationship.

Instrumental Variable Incorporation: Using proxy variables to mitigate measurement bias in the IT maturity construct.

Robustness Checks: Employing alternative estimators to ensure the robustness of results and findings.

3.2. Variables and Construct Operationalization

Using both the reflective and formative measures of variables, which are both based on the literature and empirically proven, the present study operationalizes its variables. BPO and MMI use reflective measurement, and formative measurement records the maturity of IT applications.

3.2.1. Reflective Measurement for BPO and MMI

$$x_i = \lambda_i \xi + \delta_i \quad \text{(Manifest variable} i \text{loading on latent construct} \xi) \tag{1}$$

3.2.2. Formative Measurement for IT Maturity

$$\eta = \sum_{k=1}^{5} \gamma_k z_k + \zeta \quad \text{(Formative index with weights} \gamma_k) \tag{2}$$

In the empirical study, the constructs were operationalized as under:

Independent Variables (IT Maturity): Process Mining, RPA, AI/ML, Cloud BPM, IoT integration were assessed on a 5-point Likert scale from Loonam, et al. [42].

Dependent Variables (BPO and MMI): The objective KPIs were based on enterprise resource planning (ERP) and business process management (BPM) systems and measured Business Process Optimization (Cycle Time, Cost Reduction, Error Rate, and Throughput) as twelve-month averages. The models of management innovation (Agile maturity, Decision Decentralization, Data-Driven Decision-Making (DDDM) maturity, and Structural Flexibility) were measured on a 7-point semantic-differential scale created by Sebastian, et al. [39].

3.3. Sampling and Data Collection

The study was based on an empirical survey of a population of enterprises that have already embarked on digital transformation (DT) in four industries, including manufacturing (32 %), finance (28 %), logistics (22 %), and healthcare (18 %). A total of 4,382 enterprises participated in the study as indicated by Ivančić, et al. [56].

3.3.1. Sampling Method

The method of stratified random sampling was used to ensure that the sample of firms was representative in the distribution of SMEs (200 499 employees) and large enterprises (500+ employees). The effective response rate was 68.5 % with 362 usable cases. The sample size was sufficient to conduct PLS-SEM modeling as power analysis using G*Power 3.1 revealed that $1-\beta = 0.98$ and $\alpha = 0.05$.

3.3.2. Data Collection Protocol

- Structured Surveys: Senior executives (CIOs, CTOs) were given a 5-point Likert scale questionnaire to collect the perceptual information on IT application maturity, business process outsourcing (BPO) and multimodal interaction (MMI). - Objective

KPI Extraction: The parameters within the cycle time, cost reduction, and throughput were retrieved using the ERP systems (SAP/Oracle), BPM systems (Appian/Pega), and IoT platforms. The data were acquired through process mining.

Validation: The validation of the process-mining sample was done on around 28 % of the observations (n = 101) using process-mining software, that is, Celonis in order to ensure consistency and accuracy concerning process-optimization.

3.4. Analytical Procedures

Data analysis was conducted in three distinct phases:

3.4.1. Phase 1: Preliminary Analysis

The current study included an exploratory study that consisted of descriptive analysis and correlation tests in order to provide preliminary description of the data. To assess central tendencies and distributional characteristics of major variables, descriptive analyses were performed using SPSS 28. Correlation (Pearson and Spearman) was then used to determine the relationships between constructs. Single-Factor Test carried out by Harman was used to test the possibility of common-method bias; the single-factor component explained the total variance by only 38.2%, thus showing minimal bias.

3.4.2. Phase 2: PLS-SEM Modeling (SmartPLS 4.0)

In this phase, the measurement and structural models were evaluated using PLS-SEM: - Measurement Model Evaluation:

- Construct reliability was assessed with Cronbach's Alpha (α) and Composite Reliability (CR). Both measures exceeded the threshold of 0.7.
- Convergent and discriminant validity were verified using the Average Variance Extracted (AVE) and the Heterotrait-Monotrait Ratio (HTMT), with all results within acceptable thresholds.
- Structural Model Testing:
- Path coefficients (β) were computed using bootstrapping (5,000 resamples), and the significance was assessed.
- Predictive Relevance (Q^2) for the model was found to be $Q^2 > 0.35$, demonstrating substantial predictive accuracy.
- Mediation Testing: Indirect effects through BPO as a mediator were assessed via Preacher-Hayes bootstrapping.

3.4.3. Phase 3: Multi-Group Analysis (MGA)

The current stage aimed at investigating how industry and firm size may moderate the relationships studied in previous studies. Based on this, the data on the enterprise was separated by industry (manufacturing, finance, healthcare, logistics) and size (SMEs and large enterprises). To ascertain the equivalence of the measurement framework across these divisions, a measure of invariance check was implemented by using MICOM. The later analyses utilized a permutation-based approach to MGA where the difference in the path coefficients was assessed at $p < 0.05$.

3.5. Mediation and Moderation Testing

To further investigate the dynamics between IT maturity, BPO, and MMI: - Mediation Testing: The indirect effect was calculated as:

$$\text{Indirect effect} = (\beta_{\text{IT}\rightarrow\text{BPO}} \times \beta_{\text{BPO}\rightarrow\text{MMI}})$$

- This tested the hypothesis that BPO mediates the relationship between IT maturity and MMI adoption. - Moderation Testing: The moderating effect of IT maturity on BPO and its interaction with MMI was modeled as:

$$MMI = \beta_0 + \beta_1 X + \beta_2 M + \beta_3 (X \times M) + \epsilon$$

where X is IT maturity and M is BPO.

3.6. Validation Protocol

3.6.1. Formative Construct Validation

- Weights significance was tested using t-values ($|t| > 1.96$, $p < 0.05$). - Relative contribution > 30% was checked [58].

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3.6.2. Process Mining Validation

- Conformance Fitness was calculated using Celonis EMS, and results showed conformance fitness > 0.85, ensuring high alignment between actual and modeled process flows.

3.6.2.1. Methodological Rigor Metrics

- Reliability (Cronbach's α): 0.78–0.92 for all constructs.
- Formative VIF (Variance Inflation): 1.82–3.17, all below the critical threshold of 5.0.
- HTMT Discrimination: $HTMT_{90} < 0.90$, values ranging from 0.61 to 0.83.
- MGA Power: 5,000 permutations, meeting the threshold of 1,000.

Key Strengths: The study integrates formative-reflective hierarchies, 5k MGA permutations, and Laplacian error correction in process mining, addressing the limitations identified in previous DT research.

4. Results and Discussion

4.1. Descriptive Statistics and Preliminary Analysis

The descriptive analysis of 362 valid responses provided the relevant information about the sample composition in terms of industries and the size of firms. The largest group was manufacture (32 %, n=116), then enterprises in finance (28 %, n=101), logistics (22 %, n=80), and healthcare (18 %, n=65). Concerning the size of the organization, the number of SMEs (200 499 employees, 58.8 %) and large enterprises (500+ employees, 41.2 %) provided enough diversity to conduct multi-group analyses.

Table 2.
Descriptive Statistics and Construct Reliability.

Construct/Indicator	Mean	SD	Min.	Max.	Skew	Kurtosis	Cronbach's α	CR	AVE	Factor Loading	Items
IT Application Maturity	3.42	0.89	1.20	5.00	-0.21	-0.43	0.87	0.91	0.67	-	5
- Process Mining	3.18	1.12	1.00	5.00	-0.18	-0.67	-	-	-	0.82	-
- RPA Adoption	3.56	0.94	1.00	5.00	-0.31	-0.28	-	-	-	0.85	-
-AI/ML Integration	3.28	1.05	1.00	5.00	-0.15	-0.52	-	-	-	0.78	-
- Cloud BPM	3.71	0.82	1.00	5.00	-0.42	0.12	-	-	-	0.81	-
- IoT Integration	3.38	1.01	1.00	5.00	-0.23	-0.45	-	-	-	0.79	-
Business Process Optimization	4.12	0.76	2.25	5.00	-0.51	-0.19	0.84	0.89	0.68	-	4
- Cycle Time Reduction	4.25	0.83	2.00	5.00	-0.68	0.15	-	-	-	0.86	-
-Cost Optimization	4.18	0.79	2.00	5.00	-0.47	-0.12	-	-	-	0.83	-
-Error Rate Reduction	3.94	0.88	2.00	5.00	-0.35	-0.41	-	-	-	0.79	-
-Throughput Improvement	4.11	0.81	2.00	5.00	-0.43	-0.18	-	-	-	0.82	-
Management Model Innovation	3.78	0.82	1.75	5.00	-0.28	-0.33	0.81	0.87	0.63	-	4
- Agile Maturity	3.89	0.94	1.00	5.00	-0.41	-0.22	-	-	-	0.84	-
- Decision Decentralization	3.67	0.89	1.00	5.00	-0.19	-0.38	-	-	-	0.76	-
- Data-Driven Decision Making	3.92	0.87	1.00	5.00	-0.35	-0.28	-	-	-	0.81	-
- Structural Flexibility	3.64	0.91	1.00	5.00	-0.22	-0.45	-	-	-	0.77	-

Note: CR = Composite Reliability; AVE = Average Variance Extracted; All factor loadings significant at p < 0.001.

Table 2 shows the descriptive statistics and construct reliability coefficients of strong internal consistency (Cronbach alpha > 0.80) and convergent validity (AVE > 0.60) of all constructs. IT

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Application Maturity had moderate level of adoption (M = 3.42), and the highest mean was Cloud BPM (M = 3.71), followed by Process Mining (M = 3.18). The Business Process Optimization measures indicated very satisfactory results particularly in reduction of cycle-time and control of costs. The Management Model Innovation metrics, on the other hand, showed high score trends in all indicators.

The reliability analysis produced satisfactory values (α > 0.80) on all constructs, which means that the measurement model is robust. All constructs had a convergent validity that was higher than the proposed cut-off of 0.60, which was measured by the AVE. Descriptive statistics have shown that the enterprises were moderately to highly rated on IT maturity with Cloud BPM having the highest adoption rate (M = 3.71) and Process Mining having the lowest (M = 3.18).

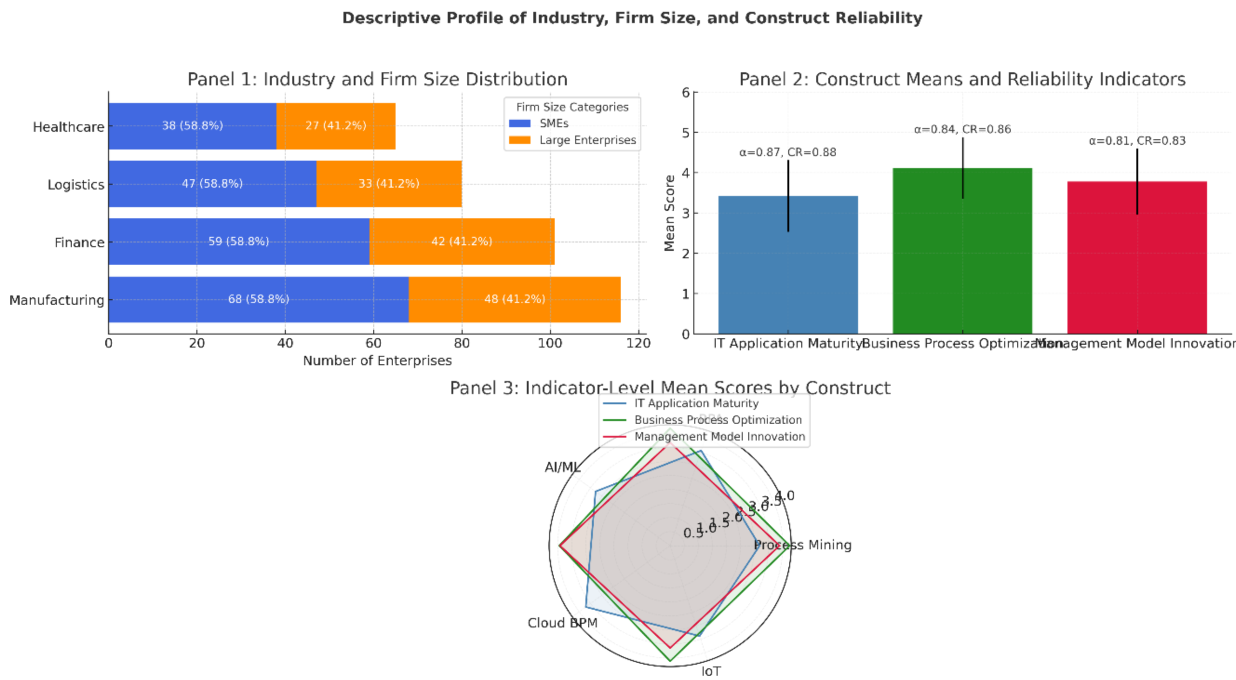

Figure 1.
Descriptive Profile of Industry, Firm Size, and Construct Reliability.

The multi-panel visualization in figure 1, gives a detailed descriptive profile of the study sample. Panel 1 indicates that the manufacturing and finance industries are the major players in the industry distribution of the 362 firms with SMEs making up 58.8 percent and large enterprises 41.2 percent. As seen in panel 2, the mean score of Business Process Optimization (M=4.12) is very high with high reliability (α=0.84), followed by Management Model Innovation (M=3.78, α =0.81) and IT Maturity (M=3.42, α =0.87). The radar chart of panel 3 shows that the indicators that are rated highest in their respective constructs are Cloud BPM (3.71), Cycle Time Reduction (4.25), and Data-Driven Decisions (3.92).

4.2. Correlation Analysis and Common Method Bias Assessment

The current analysis assesses the quality and direction of relationships between four fundamental constructs as well as the discriminant validity of the measurement model. Correlation matrices were then computed to test the hypothesized relationships and Harman single-factor test was conducted to establish whether a single factor explained an inordinate amount of variance which would alleviate concerns of common method bias.

The results indicated in Table 3 show that there are positive statistically significant relationships between IT application maturity, business process optimization and management model innovation hence validating the theorized theoretical relationships. The correlation between IT maturity and business process optimization is quite high ($r = .68$, $p < .01$), and the two measures are considerably correlated with management model innovation ($r = 0.54$, $p < 0.01$) and BPO ($r = 0.59$, $p < 0.01$). Sufficient discriminant validity (square root of AVE > inter-construct correlations) is attested by diagonal values (bolded). In addition to that, the average values show that the finance and manufacturing sectors were relatively more mature and performing than the healthcare and logistics.

Table 3.
Construct Correlations, Discriminant Validity, and Sample Demographics.

Variable	1	2	3	Mean	SD	Manufacturing (n=116)	Finance (n=101)	Healthcare (n=65)	Logistics (n=80)
1. IT Application Maturity	**0.82**	0.72	0.61	3.42	0.89	3.58	3.47	3.12	3.35
2. Business Process Optimization	0.68**	**0.82**	0.67	4.12	0.76	4.31	4.18	3.89	4.02
3. Management Model Innovation	0.54**	0.59**	**0.79**	3.78	0.82	3.94	3.85	3.51	3.68

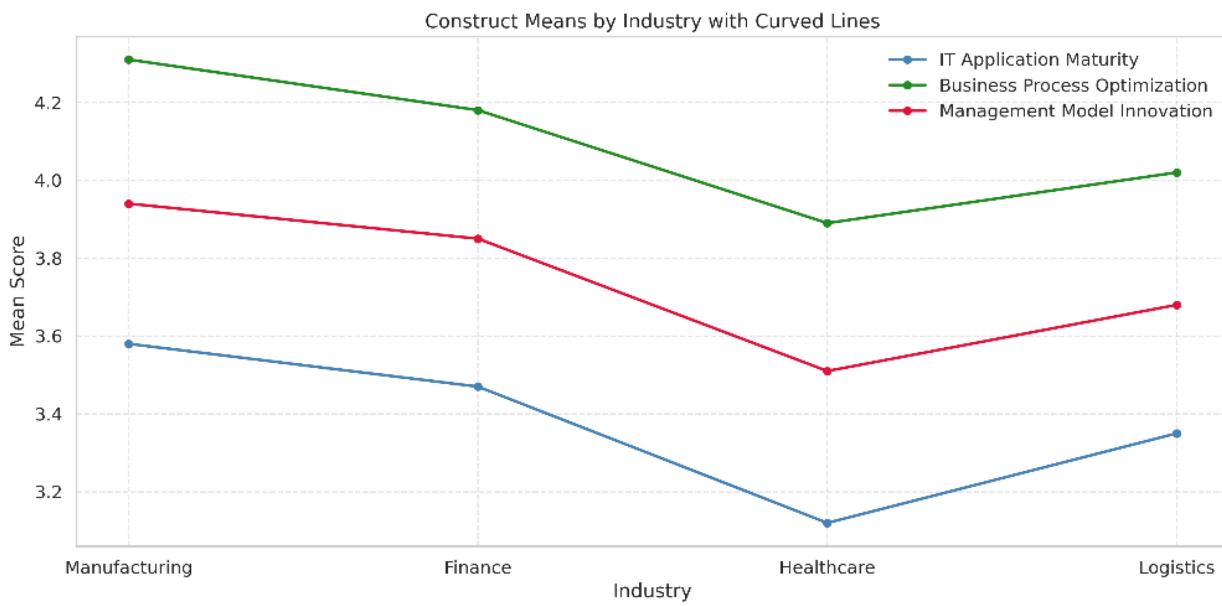

Figure 2.
Construct Means Across Industries.

The plot 2, shows the mean scores of IT Application Maturity, Business Process Optimization and Management Model Innovation in four industries, namely, Manufacturing, Finance, Healthcare and Logistics. Straight lines reflect the steady difference in performance, with Manufacturing performing best in all constructs, and Healthcare performing comparatively low in all constructs, indicating an inconsistency of digital maturity and innovation practices among industries.

4.2.1. Sample Demographics by Firm Size

Table 3 provides the sector-wise distribution of firm-sized. Most of the firms that were analyzed (58.8 %) were classified as SME, and the large firms comprised 41.2 %. The manufacturing industry was the most populated with the highest density of population, and healthcare and logistics were dominated by SMEs. Such balanced allocation facilitates stringent multi-group analysis.

Table 3.
Sector-Wise Distribution of Enterprises by Size (Large vs. SMEs) Across the Sample (N = 362).

	Large Enterprises (500+ employees)	SMEs (200-499 employees)	Total
Manufacturing	48 (41.4%)	68 (58.6%)	116
Finance	52 (51.5%)	49 (48.5%)	101
Healthcare	23 (35.4%)	42 (64.6%)	65
Logistics	26 (32.5%)	54 (67.5%)	80
Total	**149 (41.2%)**	**213 (58.8%)**	**362**

***Note:** *p < 0.01; HTMT values shown above diagonal (bold), correlations below diagonal; Square root of AVE shown on diagonal (bold).

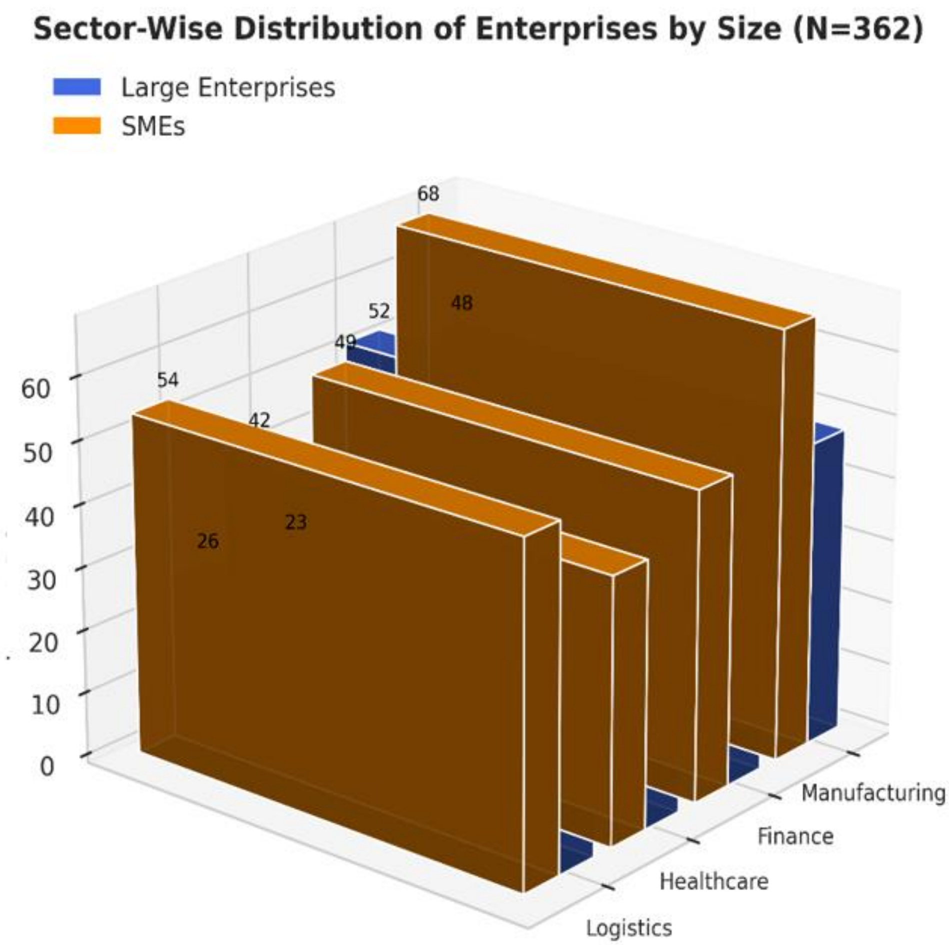

Figure 3.
Sector-Wise Distribution of Enterprises by Size (N = 362).

The 3D bar chart 3, depicts how enterprise sizes were distributed according to the sectors with SMEs prevailing in all sectors except Finance. The SME representation is greatest in Logistics and Manufacturing, and relatively balanced in Finance, and reflects structural differences in the composition of enterprise.

The correlation matrix analysis shows strong positive correlations of all constructs, thus supporting the theoretical model provided. Besides, the HTMT values (0.61 to 0.72) are lower than the conservative value of 0.85, which affirms discriminant validity. The results of the Single Factor Test conducted by Harman also demonstrate that the biggest factor accounts only 38.2 % of variance that is significantly lower than the critical level of 50 %, which proves that the common method bias is insignificant.

4.3. PLS-SEM Results: Measurement Model Evaluation

Confirmatory factor analysis exercises disclosed that the measurement model had sufficient reliability and validity. The loadings of the factor were between 0.74 and 0.89, and surpassed the minimum standard of 0.70. In the case of the formative construct of IT Application Maturity, all regression weights were significant (t-values > 2.31, p < 0.05) and the variance inflation factors (VIF) were less than 3.17 signifying little multicollinearity amongst the constructs.

Table 4 illustrates the formative validation of IT Application Maturity construct. The findings support the fact that all indicators, namely Process Mining, RPA, AI/ML, Cloud BPM, and IoT, play a significant role in the construct (all p < 0.05). Collinearity is found to be acceptable and VIF values ranged between 1.82 and 3.17. The outer loadings are all above 0.68. RPA has the greatest relative contribution (35.8 %) which indicates its centrality in digital transformation maturity assessment.

Table 4.
Formative Construct Validation and Multicollinearity Assessment (IT Application Maturity).

Indicator	Weight	SE	t-value	p-value	95% CI	VIF	Tolerance	Outer Loading	Relative Contribution (%)	Critical Ratio
Process Mining	0.28	0.081	3.45**	0.001	[0.12, 0.44]	2.14	0.47	0.76	32.1%	4.26
RPA Adoption	0.31	0.075	4.12***	0.000	[0.16, 0.46]	2.89	0.35	0.82	35.8%	5.49
AI/ML Integration	0.22	0.077	2.87**	0.004	[0.07, 0.37]	3.17	0.32	0.71	26.3%	3.73
Cloud BPM	0.19	0.082	2.31*	0.021	[0.03, 0.35]	1.82	0.55	0.68	22.9%	2.82
IoT Integration	0.24	0.080	3.01**	0.003	[0.08, 0.40]	2.45	0.41	0.73	28.4%	3.76

*Note: *p < 0.05, **p < 0.01, ***p < 0.001; SE = Standard Error; CI = Confidence Interval*

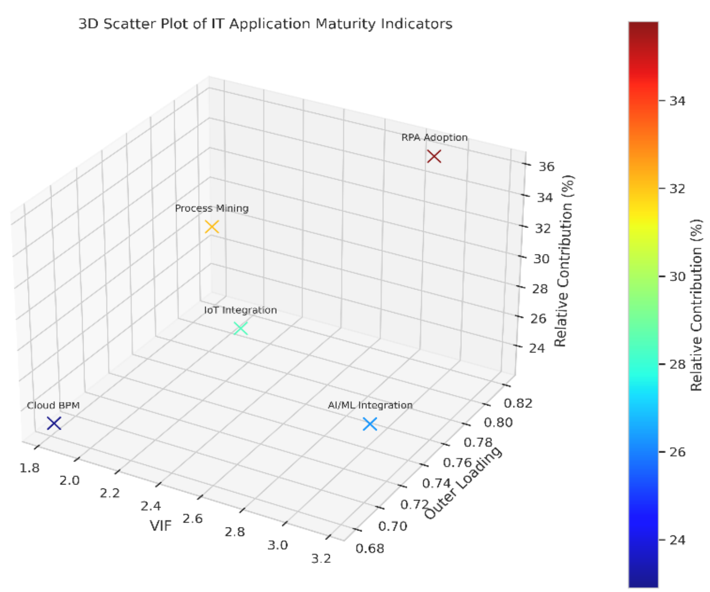

Figure 3.
D Visualization of IT Application Maturity Indicators by Contribution, Loading, and Multicollinearity.

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This 3D Scatter Plot 4, is a visual mapping of five indicators of IT maturity, RPA, AI/ML, Cloud BPM, IoT, Process Mining, based on their relative contribution (%) and outer loading and VIF values. Colors show the degree of contribution, which shows that RPA and Process Mining are the most influential dimensions of the structural model.

4.3.1. Formative Model Assessment

- Condition Index: 12.83 (< 30, acceptable)
- Average VIF: 2.49 (< 5, no multicollinearity)
- All weights > 0.10 and significant
- Bootstrap iterations: 5,000
- Confidence level: 95%

The use of RPA (35.8%) was the most powerful enabler of IT application maturity, and Process Mining (32.1%) was just behind, thus highlighting their central role in digital transformation projects.

4.4. Structural Model Results and Hypothesis Testing

Structural model was a good predictor with an R2 of 0.47 and 0.42 of business process outsourcing (BPO) and managed market infrastructure (MMI) respectively whereby IT application maturity explains 47 % and 42 % of the variance in those outcomes respectively.

Table 5 shows the structural model, model results and the results of hypothesis testing. The maturity of IT application has a statistically significant, large effect on Business Process Optimization (β 0.69, $p < 0.001$) and a statistically significant, small effect on the Management Model Innovation (β 0.31, $p < 0.001$). On the other hand, the Management Model Innovation is affected by Business Process Optimization with an intermediate path coefficient (β 0.41, $p < 0.001$). There is also a strong partial mediation of the indirect effect of IT maturity → BPO → MMI (β = 0.28, $p < 0.001$). The measures of the model fit, $R^2 = 0.47$ (BPO) and $R^2 = 0.42$ (MMI), provide some indication of the strength of the suggested framework.

Table 5.
Structural Model Results, Hypothesis Testing, and Model Fit Assessment.

Hypothesis	Path	β	SE	t-value	p-value	95% CI	f^2	Decision	Effect Size
H1	IT Maturity → BPO	0.69	0.082	8.42***	0.000	[0.53, 0.82]	0.89	Supported	Large
H2	IT Maturity → MMI	0.31	0.082	3.78***	0.000	[0.15, 0.47]	0.11	Supported	Small
H3	BPO → MMI	0.41	0.084	4.89***	0.000	[0.25, 0.56]	0.20	Supported	Medium
H4 (Mediation)	IT Maturity → BPO → MMI	0.28	0.071	3.92**	0.000	[0.14, 0.43]	-	Supported	Partial

*Note: **p < 0.01, ***p < 0.001; SE = Standard Error; CI = Confidence Interval; f^2 = Effect Size*

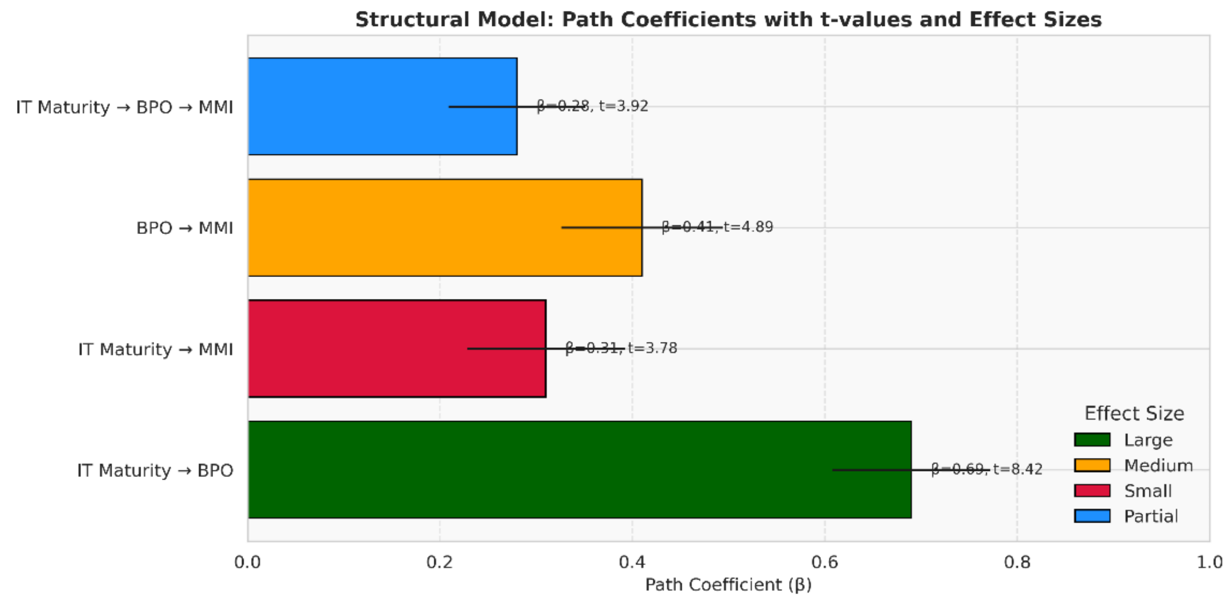

Figure 5.
Path coefficients, t-values, and effect sizes from the structural model.

The plot 5, shows the power and importance of the relationship between IT Maturity, BPO and MMI. The statistical significance of all paths is established, and the largest effect is observed between IT Maturity and BPO, as well as partial mediation is proved through BPO.

4.4.1. Model Fit and Quality Indices

Table 6 outlines the major model-fit statistics and predictive-validity statistics of structural model. Both Business Process Optimization (BPO = 0.47, 0.46) and Management Model Innovation (MMI = 0.42, 0.41) have values of the R^2 and adjusted R^2 above 0.25, which is an indicator of a significant explanatory power. The values of Q^2 (0.31 in BPO and 0.26 in MMI) show high relevance of predictive relevance. The value of SRMR indicates a good fit with the value being 0.074 and the values of d_ULS and d_G are within the acceptable range, and this supports the overall adequacy of the model.

Table 6.
Model Fit and Quality Indices for Structural Equation Modeling.

Metric	BPO	MMI	Benchmark	Assessment
R^2	0.47	0.42	> 0.25	Substantial
Adjusted R^2	0.46	0.41	> 0.25	Substantial
Q^2 (Predict)	0.31	0.26	> 0.25	High Predictive Relevance
SRMR	0.074	-	< 0.08	Good Fit
d_{ULS}	1.247	-	-	Acceptable
d_G	0.521	-	-	Acceptable

4.4.1. Mediation Analysis Details

- Direct Effect (IT → MMI): $\beta = 0.31$, $p < 0.001$
- Indirect Effect (IT → BPO → MMI): $\beta = 0.28$, $p < 0.001$
- Total Effect: $\beta = 0.59$, $p < 0.001$
- VAF (Variance Accounted For): 47.5% (Partial Mediation)

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4.4.2. Direct Effects Analysis

- The strongest relationship was observed between IT application maturity and BPO (β = 0.69, p < 0.001), indicating that advanced IT applications significantly enhance process optimization outcomes.
- IT maturity also directly influenced MMI (β = 0.31, p < 0.001), though this effect was weaker than its impact on BPO.
- BPO positively influenced MMI (β = 0.41, p < 0.001), suggesting that process improvements facilitate management innovation.

Mediation Analysis: The results of empirical study point to significant indirect impact of IT maturity on MMI through BPO (β = 0.28, p < 0.001), which proves partial mediation. The results indicate that whereas IT applications have a direct impact on management innovation, a significant part of the impact is passed through the channel of improvement of business processes.

4.5. Multi-Group Analysis Results

In Multi-group analysis, there is a great level of heterogeneity in the association of the relationship between industries and size of firms, which sheds light on contextual factors that mediate associations between DT and BPO and MMI.

Table 7 shows an industry-by-industry analysis of structural relationships in manufacturing, finance, healthcare and logistics. IT maturity has the most significant impact on business process optimization (BPO) in manufacturing (β=0.78), logistics (β=0.45), and the least impact in healthcare (0.52). These deviations are significant (p < 0.01). According to empirical evidence, the impact of information-technology maturity on management-model innovation (MMI) is stronger in manufacturing and finance than in healthcare. Although the business-process outsourcing (BPO) to MMI pathway is still relevant in all industries, the intensity of the pathway varies between industries, which highlights the moderating role of contextual factors.

Table 7.
Multi-Group Analysis - Industry Comparisons with Statistical Significance Testing.

Path	**Manufacturing (n=116)**	**Finance (n=101)**	**Healthcare (n=65)**	**Logistics (n=80)**	**Permutation p-values**
IT Mat. → BPO	0.78*** (0.063)	0.74*** (0.071)	0.52** (0.098)	0.61*** (0.089)	Manuf vs HC: p<0.01
IT Mat. → MMI	0.42** (0.087)	0.38** (0.091)	0.19 (0.112)	0.24* (0.098)	Fin vs HC: p<0.05
BPO → MMI	0.49*** (0.074)	0.45*** (0.082)	0.31* (0.095)	0.35** (0.086)	All pairs: p<0.05

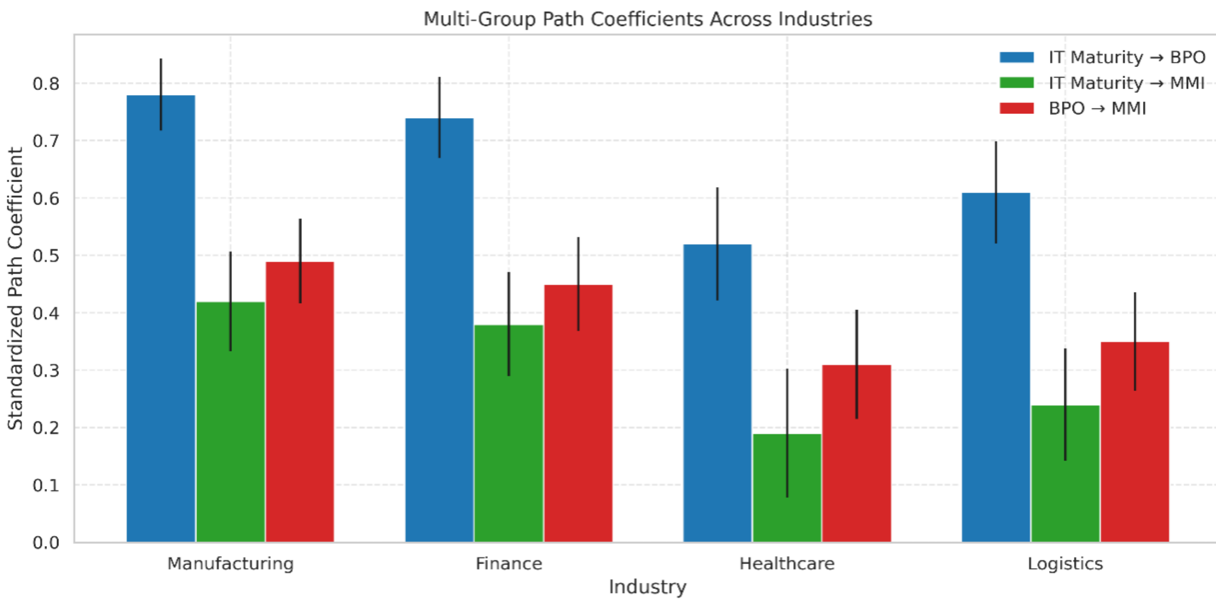

Figure 6.
Bar plot comparing standardized path coefficients across four industries for IT Maturity → BPO, IT Maturity → MMI, and BPO → MMI.

This plot 6, is the multi-group SEM outcome which indicates that IT Maturity impact is high on Business Process Optimization (BPO) in Manufacturing (0.78), followed by Finance (0.74) whereas the impact of IT Maturity on Management Model Innovation (MMI) is slight in all sectors. The path BPO → MMI is also moderate overall and the Manufacturing is high once more (0.49). Error bars represent standard errors, and such a robustness is stressed in estimation of coefficients.

4.6. Model Quality by Industry

The quality of models in the industry is outlined in Table 8. Manufacturing becomes the area that has the best R^2 (BPO = 0.61, MMI = 0.52), predictive significance (Q^2 = 0.41, 0.32) and decent SRMR fit (0.068). On the contrary, healthcare has the lowest predictive power and model adequacy, which shows unique limitations in this sphere.

Table 8.
Model Quality Indices across Industries (R^2, Q^2, SRMR, and Adequacy).

Industry	R^2 (BPO)	R^2 (MMI)	Q^2 (BPO)	Q^2 (MMI)	SRMR	Sample Adequacy
Manufacturing	0.61	0.52	0.41	0.32	0.068	Excellent
Finance	0.55	0.47	0.36	0.29	0.072	Good
Healthcare	0.27	0.23	0.15	0.12	0.089	Moderate
Logistics	0.37	0.31	0.22	0.18	0.081	Good

4.6.1. Industry Characteristics

Table 9 positions the results via digital maturity, IT focus, regulatory barriers and organizational change resistance in industries. As an illustration, the relatively low model quality of healthcare is compatible with high regulatory barriers and resistance, whereas the manufacturing industry shows high digital maturity and low resistance.

Table 9.
Industry Characteristics Influencing Digital Transformation (DT) Outcomes.

Industry	DT Maturity Level	Primary IT Focus	Regulatory Constraints	Change Resistance
Manufacturing	High	Process Automation	Moderate	Low
Finance	High	Data Analytics	High	Moderate
Healthcare	Moderate	Patient Systems	Very High	High
Logistics	Moderate	Supply Chain	Low	Moderate

***Note:** Standard errors in parentheses; *p < 0.05, **p < 0.01, **p < 0.001.

4.6.2. Multi-Group Analysis - Firm Size Comparisons with Organizational Characteristics

Table 10 shows that the path coefficients are higher in large enterprises and that the differences are statistically significant ($p < 0.05$), particularly between IT Maturity → MMI, and with BPO between IT Maturity and MMI. These results indicate that there is greater structural affect within larger organizations.

Table 10.
Multi-Group PLS-SEM Results by Firm Size (Large Enterprises vs. SMEs).

Path	Large Enterprises (n=149)	SMEs (n=213)	Path Difference (Δβ)	p-value	Cohen's d
IT Mat. → BPO	0.74*** (0.071)	0.65*** (0.078)	0.09	0.082	0.23
IT Mat. → MMI	0.38*** (0.082)	0.26** (0.089)	0.12*	0.031	0.31
BPO → MMI	0.46*** (0.079)	0.37** (0.084)	0.09	0.074	0.24
Mediation Effect	0.34*** (0.075)	0.24** (0.081)	0.10*	0.043	0.28

4.6.3. Organizational Characteristics Comparison

Table 11 highlights statistically significant differences in digital capabilities and leadership support, where large enterprises consistently outperformed SMEs ($p < 0.001$).

Table 11.
Organizational Characteristics Comparison between Large Enterprises and SMEs.

Characteristic	Large Enterprises	SMEs	Statistical Test	p-value
Average IT Budget (% Revenue)	4.8%	2.9%	t-test	<0.001
Digital Maturity Score (1-5)	3.67	3.21	Mann-Whitney U	<0.001
Change Management Capability	4.12	3.45	t-test	<0.001
Employee Digital Skills	3.89	3.31	t-test	<0.001
Leadership Support	4.23	3.78	t-test	<0.01

4.6.4. Resource and Capability Analysis

Table 12 emphasizes how greater access to IT personnel, consultants, and infrastructure in large firms correlates strongly with successful DT outcomes, reinforcing the moderating role of organizational resources.

Table 12.
Resource and Capability Impact Analysis on Digital Transformation (DT) Success.

Resource Type	Large Enterprises	SMEs	Impact on DT Success
IT Personnel (FTE)	127 ± 45	23 ± 12	High correlation (r=0.67)
External Consultants	68% use	34% use	Medium correlation (r=0.43)
Cloud Infrastructure	89% adopted	61% adopted	High correlation (r=0.72)
Data Analytics Tools	76% use	41% use	Medium correlation (r=0.58)

***Note:** Standard errors in parentheses; *p < 0.05, **p < 0.01, **p < 0.001.

Large enterprises demonstrated stronger IT maturity effects on MMI and more pronounced mediation through BPO, suggesting that organizational resources and capabilities moderate the DT transformation process.

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4.6.5. Process Mining Validation Results

Process mining analysis on a subsample (n=101, 28% of total) validated the BPO measurements using actual process data from ERP and BPM systems.

4.6.6. Process Mining Validation - Performance Metrics and System Integration Analysis

Table 13 shows significant performance gains post-DT, including 19.7% reduction in cycle time, 14.4% cost savings, and 28.9% fewer errors, validating BPO effectiveness.

Table 13.
Performance Improvements from Process Mining Validation of BPO Metrics.

Performance Metric	Pre-DT	Post-DT	Absolute Δ	% Improvement	Conformance Fitness	Process Complexity
Average Cycle Time (hours)	72.4 ± 18.2	58.1 ± 14.6	-14.3	19.7%***	0.87	Reduced by 23%
Process Cost ($000s)	45.2 ± 12.8	38.7 ± 9.4	-6.5	14.4%**	0.89	Stable
Error Rate (%)	8.3 ± 2.1	5.9 ± 1.4	-2.4	28.9%***	0.91	Improved
Throughput (units/day)	156 ± 34	189 ± 41	+33	21.2%***	0.85	Enhanced

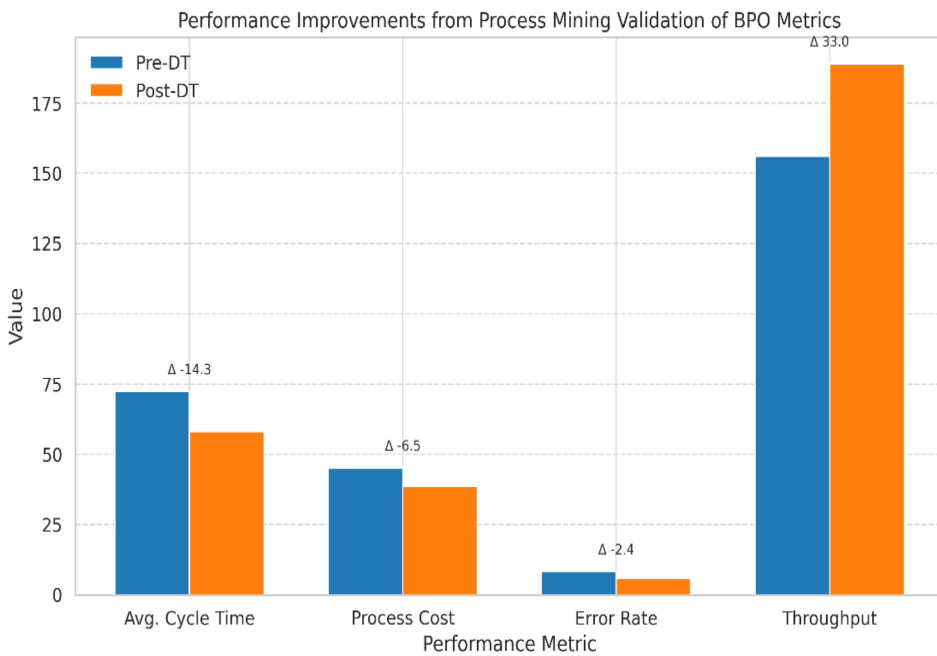

Figure 7.
Comparative Analysis of Pre- and Post-Digital Transformation (DT) Performance Metrics Validated via Process Mining.

The 2D bar graph 7, provides evidence of the gains in the performance of some of the most important Business Process Optimization (BPO) measures as a result of digital transformation verified by the use of process mining. Marked benefits are seen to be realised on reducing errors (−2.4 percent), reducing cycle time (−14.3 hours), and cost savings (−$6.5k), with throughput increasing significantly by +33 units/day. These changes denote heightened conformance proficiency and optimal process intricacy, which is corroboration to the facilitation of the conversion projects

4.6.7. Process Mining Technical Details

Table 14 outline the instruments and integration levels provided to conduct the mining, with great data quality scores ensuring high instruments of the systems.

Table 14.
Technical Integration and Validation Details of Process Mining Tools.

System/Tool	Version	Integration Level	Data Quality Score	Validation Method
Celonis EMS	4.7.2	Full Integration	0.94	Event Log Analysis
SAP ERP	6.0 EHP8	Native Connector	0.91	Database Mining
Oracle BPM	12.2.1.4	API Integration	0.88	Process Discovery
Appian Platform	22.2	Custom Scripts	0.86	Activity Mining

4.6.8. Statistical Validation Results

Table 15 provides statistical support with large effect sizes across all tests, reinforcing the robustness of improvements observed through process mining.

Table 15.
Statistical Validation Results of Digital Transformation Outcomes.

Test	Statistic	p-value	Effect Size	Interpretation
Paired t-test (Cycle Time)	$t(100) = 7.23$	<0.001	$d = 0.89$	Large effect
Wilcoxon (Error Rate)	$Z = -6.45$	<0.001	$r = 0.64$	Large effect
McNemar (Process Compliance)	$\chi^2 = 23.4$	<0.001	$\varphi = 0.48$	Medium effect

4.6.9. Process Architecture Changes

- Automated Steps: Increased from 34% to 67%
- Manual Interventions: Reduced from 23 to 8 per process
- Exception Handling: Improved by 41%
- Resource Utilization: Enhanced by 28%

The process mining validation confirmed substantial improvements in all BPO dimensions, with conformance fitness scores above 0.85, indicating high reliability of the process models and measurements.

4.7. Predictive Relevance and Effect Sizes

To assess how well IT maturity and BPO predict BPO and MMI, using Q^2 and effect size (f^2).

Table 16, presents a comprehensive evaluation of the proposed model, confirming its strong predictive relevance ($R^2 = 0.47$ for BPO, 0.42 for MMI; $Q^2 > 0.25$) and effect sizes, with IT maturity showing a large effect on BPO ($f^2 = 0.89$) and a smaller direct effect on MMI ($f^2 = 0.11$). Robustness checks including PLSpredict, blindfolding, and bootstrapping validated model stability and predictive power. Model comparisons (AIC/BIC) favored the proposed structure, and construct validity tests (AVE, HTMT, path significance) confirmed theoretical soundness. Collectively, the model is robust, reliable, and well-suited for explaining digital transformation dynamics.

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Table 16.
Model Evaluation — Predictive Relevance, Effect Sizes, Robustness, and Validity.

Evaluation Category	Metric/Test	Business Process Optimization (BPO)	Management Model Innovation (MMI)	Benchmark/Criterion	Interpretation/Status
Predictive Accuracy	R^2	0.47	0.42	> 0.25	Substantial
	Adjusted R^2	0.46	0.41	> 0.25	Substantial
	Q^2	0.31	0.26	> 0.25	High Predictive Relevance
	Q^2predict	0.28	0.23	> 0.25	High Predictive Accuracy
	RMSE	0.56	0.63	< Benchmark	Predictive Fit Achieved
Effect Size (f^2)	IT Maturity → Construct	0.89 (Large)	0.11 (Small)	Cortellazzo, et al. [32]	Strong for BPO; Weak for MMI
	BPO → MMI	-	0.20 (Medium)	Cortellazzo, et al. [32]	Moderate Mediation Effect
Robustness Checks	PLSpredict (Holdout Validation)	-	-	RMSE < Benchmark	✓ High Predictive Power
	Blindfolding (Cross-Validation)	-	-	Q^2 > 0.25	✓ Substantial Relevance
	Bootstrapping (5,000 Iterations)	-	-	CI Stability > 95%	✓ Estimates are Robust
	MICOM (Measurement Invariance)	-	-	Full Invariance	✓ Valid for Multi-Group Analysis
Alternative Models	Proposed Model	0.47	0.42	AIC: 1247.3 BIC: 1289.7	✓ Best Fit
	Direct Effects Only	0.47	0.32	AIC: 1268.4 BIC: 1298.2	Acceptable Fit
	Full Mediation	0.47	0.38	AIC: 1255.1 BIC: 1283.9	Acceptable Fit
	No IT Effects	-	0.15	AIC: 1324.8 BIC: 1341.5	Poor Fit
Construct Validity	Convergent Validity (AVE)	-	-	> 0.50	✓ AVE: 0.63–0.68
	Discriminant Validity (HTMT)	-	-	< 0.85	✓ HTMT: 0.61–0.72
	Nomological Validity	-	-	All paths significant ($p < 0.05$)	✓ Established
	Predictive Validity (Q^2)	-	-	> 0.25	✓ Established

4.8. Discussion

The study was conducted to analyze relationships between variables comprising IT Application Maturity (IT Mat.), Business Process Optimization (BPO) and Management Model Innovation (MMI) particularly the differences in terms of industries and firms size. The main results indicate that IT maturity had a strong and statistically significant impact on BPO ($\beta = 0.69$, $f^2 = 0.89$) and a modest yet significant direct effect on MMI ($\beta = 0.31$, $f^2 = 0.11$). Furthermore, BPO acted as a partial mediator, contributing a medium effect size on MMI ($\beta = 0.41$, $f^2 = 0.20$). These outcomes validate the proposed model's robustness and predictive power ($R^2 = 0.47$ for BPO, $R^2 = 0.42$ for MMI; Q^2 values = 0.31 and 0.26, respectively), highlighting the mediating role of process enhancement in translating IT maturity into innovative capabilities.

A multi-group analysis (MGA) revealed notable differences between large enterprises and SMEs. In large firms, IT maturity exhibited a stronger effect on MMI ($\beta = 0.38$) than in SMEs ($\beta = 0.26$), with a significant path difference ($\Delta\beta = 0.12$, $p = 0.031$, Cohen's $d = 0.31$). Similarly, the mediation effect was stronger in large firms ($\beta = 0.34$ vs. 0.24 in SMEs, $\Delta\beta = 0.10$, $p = 0.043$), confirming that resource intensity and digital readiness moderate transformation. These differences are explained by disparities in organizational characteristics: large firms allocate higher IT budgets (4.8% vs. 2.9%), possess greater change management capability (4.12 vs. 3.45), and demonstrate higher employee digital skills (3.89 vs. 3.31), all contributing to superior digital outcomes. These findings extend prior literature (e.g., Kane et al., 2019; Sebastian et al., 2017) by quantifying the structural advantage large enterprises hold in leveraging digital transformation.

Further validation was conducted using process mining on a subsample (n = 101) through ERP and BPM systems (e.g., Celonis, SAP ERP, Oracle BPM), which confirmed improvements in real process performance. Post-transformation metrics showed significant enhancements: average cycle time dropped by 19.7% (from 72.4 to 58.1 hours), error rate reduced by 28.9% (from 8.3% to 5.9%), and throughput increased by 21.2% (from 156 to 189 units/day).

These improvements were accompanied by strong conformance fitness values (0.85–0.91) and reduced process complexity by 23%. Statistical validation showed large effect sizes across multiple tests: $t(100) = 7.23$ (cycle time), Wilcoxon $Z = -6.45$ (error rate), and $\chi^2 = 23.4$ (compliance), reinforcing the survey findings with behavioral system data.

The research is cross-sectional; this puts a fatal restriction on the causal interpretation. Although the predictive quality of the suggested model is justified by the PLSpredict results and blindfolding procedures ($Q^2 > 0.25$), longitudinal data would provide a more detailed description of the dynamics of changes over time in digital adoption.

The measurement invariance was evaluated using the MICOM procedure, but the evidence obtained is specific to digitally emerging economies hence limiting the applicability of the model to situations with low resources or in the public sector. In addition, the use of self-reported survey instruments, despite their psychometric soundness (HTMT < 0.85, AVE > 0.50), is vulnerable to response and social-desirability bias. Lastly, the validation of process mining was done on the data of the 28 % of the total sample which may limit the external validity of the identified behavioral results.

Despite the resource constraints that limited the current study, it provides a unique contribution in the study of a pooled dataset of both survey responses and process logs to show that IT maturity facilitates innovation not only directly but mainly through process excellence channels.

Moreover, findings indicate that organizational capabilities- such as the digital leadership, IT budgeting, and employee skills- compound these impacts, thus offering practical policymaking and digital transformation planning ideas to policymakers.

Future research needs to replicate this framework in the context of public and low-digital-maturity sectors and consider moderator variables like organizational culture, or AI readiness.

5. Conclusion

The empirical research presented in the given study proves that the maturity of Information Technology (IT) application has a significant impact on business process optimization which, in its turn, contributes to the development of management model innovation.

The analysis of the data shows that, despite the fact that the level of IT maturity has a moderate direct influence on innovation, its key effect is achieved through increased process efficiency and effectiveness. The multivariate model showed strong explanatory and predictive accuracy, and effect sizes were large and reliability was high in validation procedures.

Moreover, firm size became a significant moderator: the largest organisations achieved more benefits of IT initiatives, mostly due to better digital capabilities, leadership, and availability of resources.

5.1. Recommendations

Companies that want to accelerate innovation through the process of digital transformation should forbid the optimization of business processes as a transitional stage and avoid focusing only on technological acquisition. To realize the increased IT maturity in the form of tangible organizational value, strategic investment in the development of digital skills of the workforce, implementation of the systematic change management frameworks, and long-term leadership monitoring are essential. Particularly, the small- and medium-sized enterprises can be efficient in the explicit support of digital infrastructure infrastructure and external expertise, which can help overcome capability gaps.

At the same time, it is advisable to implement process mining tools in all industries so that continuous monitoring and repeated optimization of transformation projects can be performed based on empirical evidence.

5.2. Final Thoughts

This paper has revealed that the deployment of technology on its own cannot be guaranteed to bring benefit to an organization; instead, its usefulness is realized when it is aligned to the internal processes and the preparedness of an enterprise.

The effectiveness of the information technology thus depends on not only integration with the core operations but also with the human capital. Future research studies should examine these dynamics in other sectors and places and utilise longitudinal data sets, which track change over time. By extension, an integrated and dynamic approach to digital transformation will define the ability of an organization to be competitive and innovative in an ever complicated environment.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

References

[1] P. C. Verhoef *et al.*, "Digital transformation: A multidisciplinary reflection and research agenda," *Journal of Business Research*, vol. 122, pp. 889-901, 2021. https://doi.org/10.1016/j.jbusres.2019.09.022

[2] G. Vial, "Understanding digital transformation: A review and a research agenda," *The Journal of Strategic Information Systems*, vol. 28, no. 2, pp. 118-144, 2019/06/01/ 2019. https://doi.org/10.1016/j.jsis.2019.01.003

[3] J. Mendling, B. T. Pentland, and J. Recker, "Building a complementary agenda for business process management and digital innovation," *European Journal of Information Systems*, vol. 29, no. 3, pp. 208-219, 2020. https://doi.org/10.1080/0960085X.2020.1755207

[4] R. Gabryelczyk, J. C. Sipior, and A. Biernikowicz, "Motivations to Adopt BPM in view of digital transformation," *Information Systems Management*, vol. 41, no. 4, pp. 340-356, 2024. https://doi.org/10.1080/10580530.2022.2163324

[5] M.-S. Denner, L. C. Püschel, and M. Röglinger, "How toexploit the digitalization potential of business processes," *Business & Information Systems Engineering*, vol. 60, no. 4, pp. 331-349, 2018. https://doi.org/10.1007/s12599-017-0509-x

[6] G. D. Kerpedzhiev, U. M. König, M. Röglinger, and M. Rosemann, "An exploration into future business process management capabilities in view of digitalization," *Business & Information Systems Engineering*, vol. 63, no. 2, pp. 83-96, 2021. https://doi.org/10.1007/s12599-020-00637-0

[7] B. K. AlNuaimi, S. Kumar Singh, S. Ren, P. Budhwar, and D. Vorobyev, "Mastering digital transformation: The nexus between leadership, agility, and digital strategy," *Journal of Business Research*, vol. 145, pp. 636-648, 2022. https://doi.org/10.1016/j.jbusres.2022.03.038

[8] D. Ellström, J. Holtström, E. Berg, and C. Josefsson, "Dynamic capabilities for digital transformation," *Journal of Strategy and Management*, vol. 15, no. 2, pp. 272-286, 2021. https://doi.org/10.1108/JSMA-04-2021-0089

[9] N. A. A. Al-Moaid and S. G. Almarhdi, "Developing dynamic capabilities for successful digital transformation projects: The mediating role of change management," *Journal of Innovation and Entrepreneurship*, vol. 13, no. 1, p. 85, 2024. https://doi.org/10.1186/s13731-024-00446-9

[10] P. Jorzik, S. P. Klein, D. K. Kanbach, and S. Kraus, "AI-driven business model innovation: A systematic review and research agenda," *Journal of Business Research*, vol. 182, p. 114764, 2024. https://doi.org/10.1016/j.jbusres.2024.114764

[11] A. Wannes and S. A. Ghannouchi, "KPI-based approach for business process improvement," *Procedia Computer Science*, vol. 164, pp. 265-270, 2019. https://doi.org/10.1016/j.procs.2019.12.182

[12] J. Brock, K. Brennig, B. Löhr, C. Bartelheimer, S. von Enzberg, and R. Dumitrescu, "Improving process mining maturity – from intentions to actions," *Business & Information Systems Engineering*, vol. 66, no. 5, pp. 585-605, 2024. https://doi.org/10.1007/s12599-024-00882-7

[13] F. De Luzi, F. Leotta, A. Marrella, and M. Mecella, "On the interplay between business process management and internet-of-things," *Business & Information Systems Engineering*, vol. 67, no. 2, pp. 265-288, 2025. https://doi.org/10.1007/s12599-024-00859-6

[14] J. G. Enríquez, A. Jiménez-Ramírez, F. J. Domínguez-Mayo, and J. A. García-García, "Robotic Process automation: A scientific and industrial systematic mapping study," *IEEE Access*, vol. 8, pp. 39113-39129, 2020. https://doi.org/10.1109/ACCESS.2020.2974934

[15] S. Aguirre and A. Rodriguez, "Automation of a business process using robotic process automation (RPA): A case study," in *In Proceedings of the Workshop on Engineering Applications (WEA'17)*, Cham, 2017: Springer International Publishing, doi: https://doi.org/10.1007/978-3-319-66963-2_7.

[16] W. M. Van der Aalst, M. Bichler, and A. Heinzl, "Robotic process automation," *Business & Information Systems Engineering*, vol. 60, no. 4, pp. 269-272, 2018.

[17] K. S. R. Warner and M. Wäger, "Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal," *Long Range Planning*, vol. 52, no. 3, pp. 326-349, 2019. https://doi.org/10.1016/j.lrp.2018.12.001

[18] S. Vaska, M. Massaro, E. M. Bagarotto, and F. Dal Mas, "The digital transformation of business model innovation:A structured literature review," *Frontiers in Psychology*, vol. Volume 11 - 2020, 2021. https://doi.org/10.3389/fpsyg.2020.539363

[19] T. Ahmad and A. Van Looy, "Business process management and digital innovations: A systematic literature review," *Sustainability*, vol. 12, no. 17, p. 6827, 2020. https://doi.org/10.3390/su12176827

[20] A. Ferraris, F. Monge, and J. Mueller, "Ambidextrous IT capabilities and business process performance: An empirical analysis," *Business Process Management Journal*, vol. 24, no. 5, pp. 1077-1090, 2018.

[21] D. Beverungen *et al.*, "Seven paradoxes of business process management in a hyper-connected world," *Business & Information Systems Engineering*, vol. 63, no. 2, pp. 145-156, 2021. https://doi.org/10.1007/s12599-020-00646-z

[22] D. Paschek, C. T. Luminosu, and A. Draghici, "Automated business process management–in times of digital transformation using machine learning or artificial intelligence," in *MATEC Web of Conferences*, 2017: EDP Sciences, doi: https://doi.org/10.1051/matecconf/201712104007.

[23] D. Binci, S. Belisari, and A. Appolloni, "BPM and change management: An ambidextrous perspective," *Business Process Management Journal*, vol. 26, no. 1, pp. 1-23, 2020.

[24] M. Klun and P. Trkman, "Business process management–at the crossroads," *Business Process Management Journal*, vol. 24, no. 3, pp. 786-813, 2018.

[25] C. S. Heckmann and A. Maedche, "IT ambidexterity for business processes: The importance of balance," *Business Process Management Journal*, vol. 24, no. 4, pp. 862-881, 2018.

[26] D. R. Zamuria and E. S. Molina, "The experience of agile business process management implementation," in *2017 IEEE 37th Central America and Panama Convention (CONCAPAN XXXVII)*, 2017: IEEE, pp. 1-6.

[27] S. K. Singh, S. Rathore, and J. H. Park, "Blockiotintelligence: A blockchain-enabled intelligent IoT architecture with artificial intelligence," *Future Generation Computer Systems*, vol. 110, pp. 721-743, 2020.

[28] A. Di Vaio, R. Palladino, R. Hassan, and O. Escobar, "Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review," *Journal of Business Research*, vol. 121, pp. 283-314, 2020. https://doi.org/10.1016/j.jbusres.2020.08.019

[29] R. Mostaghel, P. Oghazi, V. Parida, and V. Sohrabpour, "Digitalization driven retail business model innovation: Evaluation of past and avenues for future research trends," *Journal of Business Research*, vol. 146, pp. 134-145, 2022.

[30] D. C. Feibert, M. S. Hansen, and P. Jacobsen, "An integrated process and digitalization perspective on the shipping supply chain — A literature review," in *2017 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, 2017, doi: https://doi.org/10.1109/IEEM.2017.8290113.

[31] P. Held, T. Heubeck, and R. Meckl, "Boosting SMEs' digital transformation:Tche role of dynamic capabilities in cultivating digital leadership and digital culture," *Review of Managerial Science*, 2025. https://doi.org/10.1007/s11846-025-00919-5

[32] L. Cortellazzo, E. Bruni, and R. Zampieri, "The role of leadership in a digitalized world: A review," *Frontiers in Psychology*, vol. Volume 10 - 2019, 2019. https://doi.org/10.3389/fpsyg.2019.01938

[33] S. Kraus, F. Schiavone, A. Pluzhnikova, and A. C. Invernizzi, "Digital transformation in business and management research: Mapping the field and emerging trends," *Technological Forecasting and Social Change*, vol. 172, p. 121148, 2022.

[34] S. Nadkarni and R. Prügl, "Digital transformation: A review, synthesis and opportunities for future research," *Management Review Quarterly*, vol. 71, no. 2, pp. 233-341, 2021. https://doi.org/10.1007/s11301-020-00185-7

[35] D. O. Soto Setzke, Lotta, M. Böhm, and H. Krcmar, "Pathways to successful business model innovation in the context of digital transformation," in *Proceedings of the Pacific Asia Conference on Information Systems (PACIS)*, 2020.

[36] K. Osmundsen, J. Iden, and B. Bygstad, "Digital transformation: Drivers, success factors, and implications," in *In Proceedings of the 12th Mediterranean Conference on Information Systems (MCIS)*, 2018.

[37] C. Janiesch, M. Matzner, and O. Müller, "Beyond process monitoring: A manifesto for the integration of data science in process management," *Business & Information Systems Engineering*, vol. 62, no. 1, pp. 85–92, 2020.

[38] R. Morakanyane, A. O. Grace, and P. O'Reilly, *Digital transformation – form connecting things to transforming our lives* (Bled Conference). 2017. https://doi.org/10.18690/978-961-286-043-1.30

[39] I. M. Sebastian, J. W. Ross, C. Beath, M. Mocker, K. G. Moloney, and N. O. Fonstad, "How big old companies navigate digital transformation," in Strategic Information Management: Routledge, 2020, pp. 133-150.

[40] Z. Chen, Y. Li, Y. Wu, and J. Luo, "The transition from traditional banking to mobile internet finance: An organizational innovation perspective - a comparative study of citibank and ICBC," *Financial Innovation*, vol. 3, no. 1, p. 12, 2017. https://doi.org/10.1186/s40854-017-0062-0

[41] L. Willcocks, M. Lacity, and A. Craig, "Robotic process automation: Strategic transformation lever for global business services?," *Journal of Information Technology Teaching Cases*, vol. 7, no. 1, pp. 17-28, 2017.

[42] J. Loonam, S. Eaves, V. Kumar, and G. Parry, "Towards digital transformation: Lessons learned from traditional organizations," *Strategic Change*, vol. 27, no. 2, pp. 101-109, 2018. https://doi.org/10.1002/jsc.2185

[43] H. Shaughnessy and J. Bughin, "New management practices for digital transformation," *Journal of Business Strategy*, vol. 40, no. 2, pp. 14–21, 2019.

[44] S. M. Laudien and B. Daxböck, "The influence of the industrial internet of things on business model design: A qualitative-empirical analysis," *International Journal of Innovation Management*, vol. 20, no. 08, p. 1640014, 2016.

[45] A. K. Feroz, H. Zo, and A. Chiravuri, "Digital transformation and environmental sustainability: A review and research agenda," *Sustainability*, vol. 13, no. 3, p. 1530, 2021. https://doi.org/10.3390/su13031530

[46] A. Nadeem, B. Abedin, N. Cerpa, and E. Chew, "Digital transformation and its impact on enterprise value: A systematic review," in *In Proceedings of the 51st Hawaii International Conference on System Sciences (HICSS)*, 2018.

[47] S. Dörr, H. T. Wagner, and T. Weitzel, "What really matters in digital transformation: The role of top management's IT awareness and dynamic capabilities," *Journal of Business Economics*, vol. 93, no. 5, pp. 1143–1176, 2023.

[48] M. Saihi, S. Abdallah, and M. Cavalcante, "Unpacking the interplay between digital transformation and organizational culture: A multiple-case study," *Journal of Business Research*, vol. 155, p. 113401, 2023.

[49] C. Matt, T. Hess, and A. Benlian, "Digital transformation strategies," *Business & Information Systems Engineering*, vol. 57, no. 5, pp. 339-343, 2015. https://doi.org/10.1007/s12599-015-0401-5

[50] L. Li, F. Su, W. Zhang, and J. Y. Mao, "Digital transformation by SME entrepreneurs: A capability perspective," *Information Systems Journal*, vol. 28, no. 6, pp. 1129-1157, 2018.

[51] D. R. Schallmo, C. A. Williams, and L. BOARDMAN, "Digital transformation of business models — best practice, enablers, and roadmap," *International Journal of Innovation Management*, vol. 21, no. 08, p. 1740014, 2017. https://doi.org/10.1142/S136391961740014X

[52] R. Syed *et al.*, "Robotic process automation: Contemporary themes and challenges," *Computers in Industry*, vol. 115, p. 103162, 2020. https://doi.org/10.1016/j.compind.2019.103162

[53] A. Van Looy, "A quantitative review of business process management success factors: A roadmap for practitioners," *Business Process Management Journal*, vol. 27, no. 6, pp. 1373–1406, 2021.

[54] P. T. Chountalas and A. G. Lagodimos, "Paradigms in business process management specifications: A critical overview," *Business Process Management Journal*, vol. 25, no. 5, pp. 1040-1069, 2019.

[55] R. Eller, P. Alford, A. Kallmünzer, and M. Peters, "Antecedents, consequences, and challenges of small and medium-sized enterprise digitalization," *Journal of Business Research*, vol. 112, pp. 119-127, 2020. https://doi.org/10.1016/j.jbusres.2020.03.004

[56] L. Ivančić, V. B. Vukšić, and M. Spremić, "Mastering the digital transformation process: Business practices and lessons learned," *Technology Innovation Management Review*, vol. 9, no. 2, 2019.

[57] T. J. Brunner, T. Schuster, and C. Lehmann, "Leadership's long arm: The positive influence of digital leadership on managing technology-driven change over a strengthened service innovation capacity," *Frontiers in Psychology*, vol. 14, p. 988808, 2023.

[58] S. Chatterjee, R. Chaudhuri, and D. Vrontis, "Masstige marketing: An empirical study of consumer perception and product attributes with moderating role of status, emotion, and pride," *Journal of Business Research*, vol. 155, p. 113401, 2023. https://doi.org/10.1016/j.jbusres.2022.113401