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ARTICLE

From It Maturity to Competitive Intelligence: How Digital Transformation Drives Process Optimization and Management Innovation

Da Maturidade em TI à Inteligência Competitiva: Como a Transformação Digital Impulsiona a Otimização de Processos e a Inovação na Gestão

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ABSTRACT | Purpose: This study investigates how digital transformation contributes to organizational competitive intelligence by examining the relationships among Information Technology (IT) application maturity, Business Process Optimization (BPO), and Management Model Innovation (MMI). The objective is to explain how digital capabilities evolve from operational improvements into decision-relevant intelligence that supports strategic management. **Methodology/approach:** A quantitative-dominant mixed-methods design was adopted, combining survey data and objective system-level performance indicators from 362 firms operating in manufacturing, finance, healthcare, and logistics sectors. Partial Least Squares Structural Equation Modeling (PLS-SEM), multi-group analysis, and mediation testing were employed to assess causal relationships. Process mining techniques were used to validate operational performance improvements based on ERP and BPM system data. **Originality/Relevance:** The study advances digital transformation research by explicitly conceptualizing it as a competitive intelligence capability rather than a purely technological or efficiency-oriented phenomenon. By integrating IT maturity, process optimization, and management innovation within a unified analytical framework, the research addresses critical gaps in empirical and methodological literature. **Key findings:** Results indicate that IT application maturity has a strong positive effect on business process optimization and a moderate direct effect on management model innovation. Business process optimization partially mediates this relationship, confirming that structured and traceable processes are central to transforming digital capabilities into managerial intelligence. Sectoral differences were also identified. **Theoretical/methodological contributions:** The study provides an empirically validated framework linking digital

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transformation to competitive intelligence through sequential capability building. Methodologically, it strengthens rigor by integrating PLS-SEM, multi-group analysis, and process mining to bridge operational data with strategic decision-making.

Keywords | Digital Transformation. Information Technology Applications. Business Process Optimization. Management Model Innovation. PLS-SEM. Multi-Group Analysis. Process Mining.

RESUMO | Objetivo: Este estudo investiga como a transformação digital contribui para a inteligência competitiva organizacional, analisando as relações entre maturidade das aplicações de Tecnologia da Informação (TI), Otimização de Processos de Negócio (OPN) e Inovação no Modelo de Gestão (IMG). O objetivo é explicar como as capacidades digitais evoluem de ganhos operacionais para inteligência relevante à tomada de decisão estratégica. **Metodologia/abordagem: Adotou-se um desenho de métodos mistos com predominância quantitativa,** combinando dados de survey e indicadores objetivos de desempenho de sistemas, obtidos junto a 362 empresas dos setores de manufatura, finanças, saúde e logística. Foram utilizados Modelagem de Equações Estruturais por Mínimos Quadrados Parciais (PLS-SEM), análise multigrupos e testes de mediação. Técnicas de *process mining* foram aplicadas para validar melhorias operacionais com base em dados de sistemas ERP e BPM. **Originalidade/Relevância:** O estudo avança a literatura ao conceituar explicitamente a transformação digital como uma capacidade de inteligência competitiva, e não apenas como um fenômeno tecnológico ou de eficiência operacional. A integração entre maturidade em TI, processos e inovação gerencial preenche lacunas teóricas e empíricas relevantes. **Principais resultados:** Os resultados indicam que a maturidade em TI exerce forte influência positiva sobre a otimização de processos e um efeito direto moderado sobre a inovação no modelo de gestão. A otimização de processos atua como mediadora parcial, evidenciando seu papel central na conversão de capacidades digitais em inteligência gerencial. Diferenças setoriais também foram identificadas. **Contribuições teóricas/metodológicas:** O estudo propõe um framework empiricamente validado que conecta transformação digital e inteligência competitiva por meio de capacidades sequenciais. Metodologicamente, contribui ao integrar PLS-SEM, análise multigrupos e *process mining*, conectando dados operacionais à tomada de decisão estratégica.

Palavras-chave | Transformação digital. Aplicações de tecnologia da informação. Otimização de processos de negócio. Inovação no modelo de gestão. PLS-SEM. Análise multigrupos. Mineração de processos.

1 INTRODUÇÃO

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 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 Denner et al. (2018); Gabryelczyk et al. (2024); Kerpedzhiev et al. (2021); Mendling et al. (2020); Verhoef et al. (2021); Vial (2019).

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) (AlNuaimi et al., 2022; Ellström et al., 2022), 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 (Al-Moaid & Almarhdi, 2024).

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 (Jorzik et al., 2024; Wannes & Ghannouchi, 2019; Brock et al., 2022) References. 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 (De Luzi et al., 2025; Enríquez et al., 2020; Aguirre & Rodriguez, 2017; van der Aalst et al., 2018; Warner & Wäger, 2019) (De Luzi et al., 2025; Enríquez et al., 2020; Aguirre & Rodriguez, 2017; van der Aalst et al., 2018; Warner & Wäger, 2019).

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 (Vaska et al., 2020). A considerable share of existing empirical studies is 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 (Ahmad & Van Looy, 2020 ;Ferraris et al., 2018;Beverungen et al., 2020). Insights on the findings can be used by decision-makers in the emerging markets to design 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 analyze the relationships between IT application maturity, business process optimization, and management model innovation using PLS-SEM.
2) To examine the mediating role of business process optimization in linking IT maturity with management model innovation.
3) To evaluate sectoral and organizational size differences in the IT–BPO–MMI relationships through multi-group analysis.
4) To validate process-level performance improvements using process mining based on ERP and BPM system data.
5) To develop an empirically grounded framework explaining how digital capability translates into intelligence-enabled managerial transformation.

This study further develops the discussion of digital transformation by providing empirical evidence of a synthesized theoretical approach that interconnects the IT application maturity, business process optimisation, and management model innovation. Using the Partial Least Squares Structural Equation Modelling (PLS -SEM) and process-mining-driven validation, the findings indicate that the business process optimisation is a key mediator between the transformation of digital capabilities into managerial innovation. It is also indicated in the analysis that sectoral and firm-size differentiation is explained through multi-group comparisons. The combination of system-generated performance measures with structural modelling, enables the research to increase methodological rigor and provide a pragmatically oriented, intelligence-driven framework that enables strategic alignment of digital investments, process efficiency and organizational innovation.

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.

This research places competitive intelligence at the centre of the theoretical architecture and conceptualises the digital transformation as an organisational construct that enhances the competitive intelligence capability. In particular, IT application maturity, business process optimisations and management model innovations are theorised as linked strata facilitating strategic sensing, intelligence processing and data-driven decision making. As a result, the suggested model is investigating the fact that digital transformation fosters a competitive positioning focused on competitive intelligence through the development of capabilities inherent in processes and management hierarchies.

2 LITERATURE REVIEW

2.1 Digital Transformation as a Competitive Intelligence Capability

The existing literature proves that advanced information technologies are a key factor in facilitating digital transformation, but the role of these technologies in competitive intelligence is often discussed implicitly and not explicitly stated. (Jorzik et al. 2020) have shown that business-model innovation can be assisted by artificial intelligence, but the absence of longitudinal validation did not allow them to make deductive conclusions on the perpetual strategic learning. Brock et al. (2021) demonstrated that process mining contributes to business process optimisation, but stressed that the quality of data must be good to guarantee the accuracy of the intelligence obtained using operational systems. (De Luzi et al. 2021) demonstrated that the use of the IoT-conscious business process management enhances organisational agility, whereas interoperability issues limit information flows in the form of an integrated entity. (Paschek et al. 2022) affirmed that BPM automation based on machine-learning enhances the efficiency of operations, but the complexity of integration hinders scalability. In the case of qualitative analysis, (Binci et al. 2023) discovered that ambidextrous BPM enhances organisational flexibility, but the culture does not welcome the interpretation of strategic information by all. (Klun and Trkman 2024) also pointed out that digitalisation necessitates new governance patterns to promote innovation-driven coordination, and (Heckmann and Maedche 2024) suggested that IT flexibility and standardisation are the best way to ensure process resilience at the cost of unequal resource distribution. Zamuria and Molina (2024) showed that the agile BPM is responsive, but the measurement inconsistencies undermine the common intelligence generation due to sprints. (Singh et al. 2024) introduced an IoT intelligence framework using blockchain and AI, which demonstrated the data security and automation improvements, but high start-up costs are the main obstacle to adoption. In a systematic literature review, (Di Vaio et al. 2025) concluded that AI-based digital transformation is a quicker value creation and emphasizes the role of governance systems. (Mostaghel et al. 2025) have found that digitalisation leads to better customer engagement and supply-chain agility, and the outcome intensity depends on the level of digital maturity. In addition, (Feibert et al. 2025) found that IoT-cloud integration was essential in generating intelligence in digital supply chains, and interoperability continued to be a structural challenge.

To supplement these technological viewpoints, organizational-level research highlights the fact that success in digital transformation relies on the capacity to transform digital outputs into decision-relevant intelligence. Through structural equation modelling, (Held et al. 2025) established that dynamic capabilities mediate the association between digital leadership and cultural readiness in SMEs, albeit in a sectoral context, which restricts the degree of generalization. (Cortellazzo et al. 2025) revealed that transformational and participative leadership styles help support the process of IT adoption, but the broader applicability is limited by the contextual heterogeneity. With the help of bibliometric and content analysis, (Kraus et al. 2025) established the incorporation of AI, process mining, and IoT as the areas of focus of digital transformation research yet indicated the lack of longitudinal studies. In a meta-review of 200-plus studies, (Nadkarni and Prgl 2025) claimed that the successful digital transformation depends on the alignment between the adoption of technologies and the renewal of the strategy, with little empirical analysis of the links between the outcomes. (Soto Setzke et al. 2025) discovered that iterative experimentation was one of the primary sources of business-model innovation in situations of digital transformation yet measurement issues were also significant. In a similar manner, (Osmundsen et al. 2025) established that strategic vision, customer focus, and flexible IT infrastructure are key aspects that drive transformation whereas constant skills deficiency limits efficient use of intelligence outputs. Even though such contributions are made, competitive intelligence is not often imagined as a cohesive organisational capability. To fill this gap, the current research views digital transformation as a process that creates a competitive intelligence capacity by allowing IT application maturity to allow strategic sensing, business process optimisation to facilitate intelligence processing, and management model innovation to facilitate data-driven strategic decision-making and, consequently, enhancing competitive positioning.

2.2 Interplay Between Business Process Optimization and Management Model Innovation

(Janiesch et al. 2020) 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. 2017) 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. 2017) 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. 2017) 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. 2017) 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. 2018) 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 2019) 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 Daxbock 2017) 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. 2020) 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. (Dörr et al. 2023) 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. 2023) 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. 2017) 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. 2018) 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. 2017) 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.

(Syed et al. 2020) identified important measurement problems that limited the accuracy of enterprise-wide impact analysis of robotic process automation (RPA). Parallel to this, (Van Looy 2021) 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 2019) 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. 2020) 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. (Ivančic et al. 2019) 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. 2023) 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 shows the comparative study of previous literature.

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

Ref. No.	Technique / Methodology	Focus Area	Key Results	Limitations
[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
[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 (β = 0.61) for SMEs in linking DT adoption to process agility	No longitudinal tracking; sample restricted to South Asian firms
[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
[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
[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
[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

CI interpretation of the hypotheses

The hypotheses taken together imagine competitive intelligence as a capability that is embedded in digital transformation. The correlation between the IT application maturity and business process optimisation indicates the increased strategic sensing and enhanced data quality, whereas the correlation between business process optimisation and management model innovation denotes the incorporation of processed intelligence into the routine managerial processes and decision formations. The direct-between-IT maturity and management model innovation pathway represents the impact of advanced analytics on management innovation other than process redesign. With this, the mediation structure determines whether business process optimisation is the key mechanism according to which digital transformation turns into decision-relevant competitive intelligence.

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.

Reflective Measurement for BPO and MMI

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

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. (2022).
- 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 [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 IDC (2024).

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:

$$\text{Indirect effect} = \left(\beta_{\text{IT}\rightarrow\text{BPO}} \times \beta_{\text{BPO}\rightarrow\text{MMI}}\right) \tag{3}$$

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:

$$\text{MMI} = \beta_0 + \beta_1 \text{X} + \beta_2 \text{M} + \beta_3 (\text{X} \times \text{M}) + \epsilon \tag{4}$$

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 (Cenfetelli & Bassellier, 2009).

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.

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 final sample comprised 362 firms across manufacturing (n = 116), finance (n = 101), healthcare (n = 65), and logistics (n = 80). Small and medium-sized enterprises represented 58.8% of the sample, while large enterprises accounted for 41.2%. Descriptive statistics indicate moderate levels of IT application maturity (M = 3.42, SD = 0.89), high levels of business process optimization (M = 4.12, SD = 0.76), and moderately high management model innovation (M = 3.78, SD = 0.82). Detailed construct statistics and reliability indicators are reported in Table 2 and Figure 1.

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	-

Construct/Indicator	Mean	SD	Min	Max	Skew	Kurtosis	Cronbach's α	CR	AVE	Factor Loading	Items
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

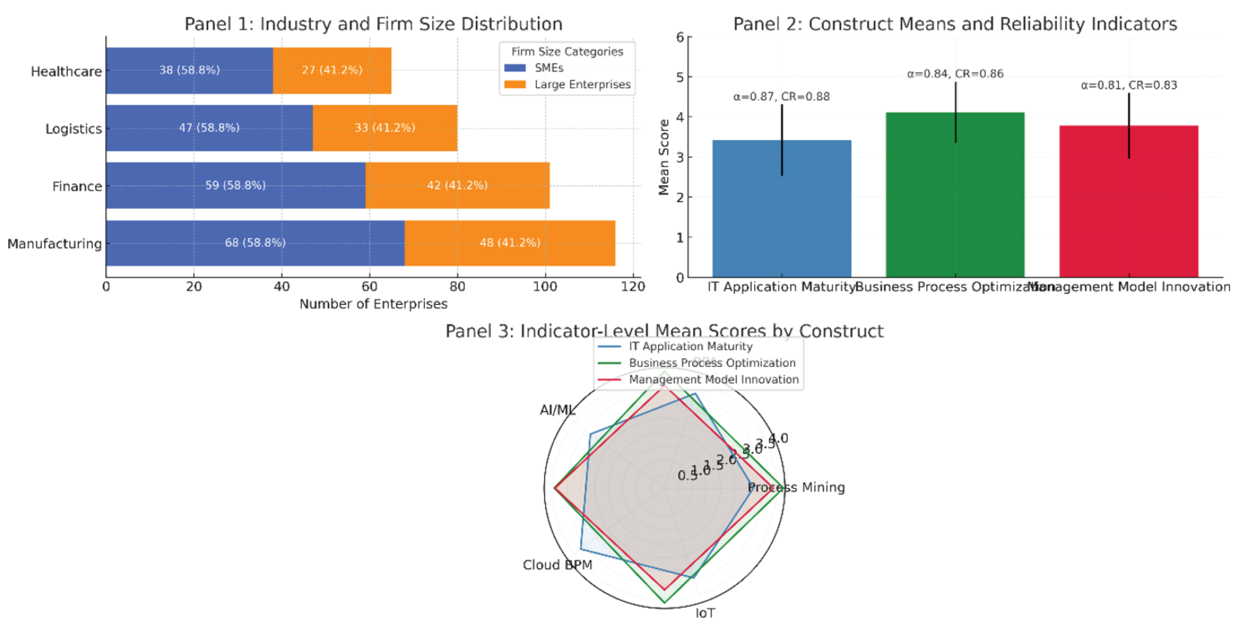

Figure 1. Descriptive Profile of Industry, Firm Size, and Construct Reliability

The 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

Table 3 show that IT application maturity, business process optimization, and management model innovation exhibit statistically significant positive association with each other, and thus, support the theoretical hypothesized correlations. The correlation of IT maturity with business process optimization is especially strong (r = -.68, p <-.01), and both variables have significant relationships with management model innovation (r -.54, p <-.01) and with BPO (r -.59, p <-.01). Sufficient discriminant validity is also demonstrated by the presence of the square roots of the average variance extracted (AVE) having greater values than inter-construct correlations, a fact that the diagonal bolded values confirm. Also, the descriptive statistics show that the finance and manufacturing sectors are characterized by rather high maturity and performance rates in comparison with the healthcare and logistics sectors.

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

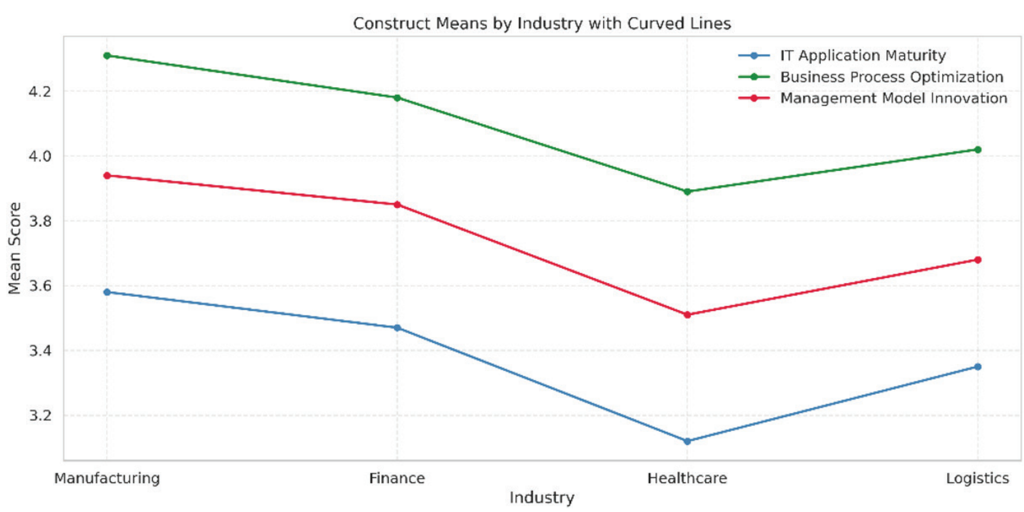

Figure 2. Construct Means Across Industries

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.

4.3 PLS-SEM Results: Measurement Model Evaluation

The measurement model had a good level of reliability and validity. All reflective constructs had alpha coefficients greater than 0.80 and composite reliability coefficients ranged between 0.87 and 0.91. The convergent validity was established, and the values of AVE were higher than the recommended 0.50. The loadings of all indicators were found to be significant ($p < 0.001$). Table 2 provides the descriptive statistics and reliability results. Formative assessment of the level of maturity of IT applications construct showed acceptable multicollinearity (variance inflation factor (VIF) values ranged between 1.82 and 3.17). The weights of the indicators were all significant ($p < 0.05$), which justifies the sufficiency of the formative specification (Table 4, Figure 3).

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

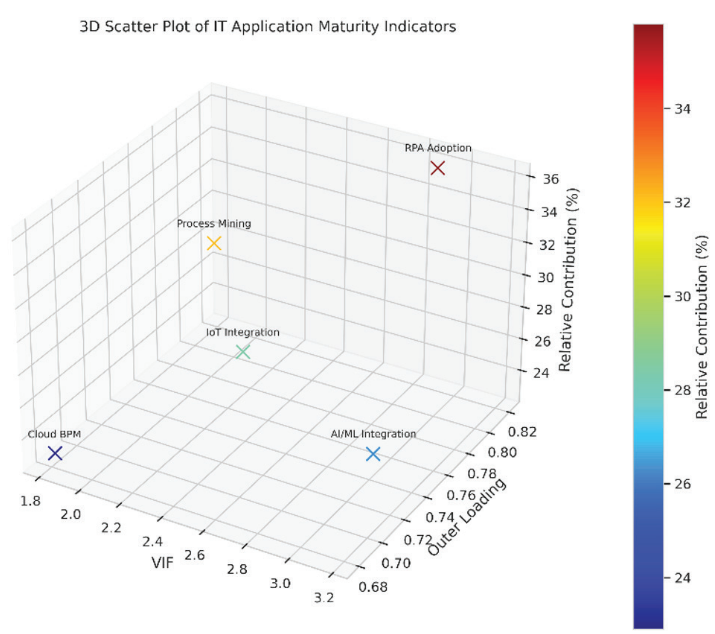

Figure 3. 3D Visualization of IT Application Maturity Indicators by Contribution, Loading, and Multicollinearity

This 3D Scatter Plot 3, 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.

4.4 Structural Model Results and Hypothesis Testing

The structural model results are summarized in Table 5 and Figure 4. IT application maturity exhibited a significant positive effect on business process optimization ($\beta = 0.69$, $p < 0.001$). A significant direct effect was also observed between IT application maturity and management model innovation ($\beta = 0.31$, $p < 0.001$). Business process optimization significantly predicted management model innovation ($\beta = 0.41$, $p < 0.001$).

The model explained 47% of the variance in business process optimization ($R^2 = 0.47$) and 42% of the variance in management model innovation ($R^2 = 0.42$), indicating substantial explanatory power.

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

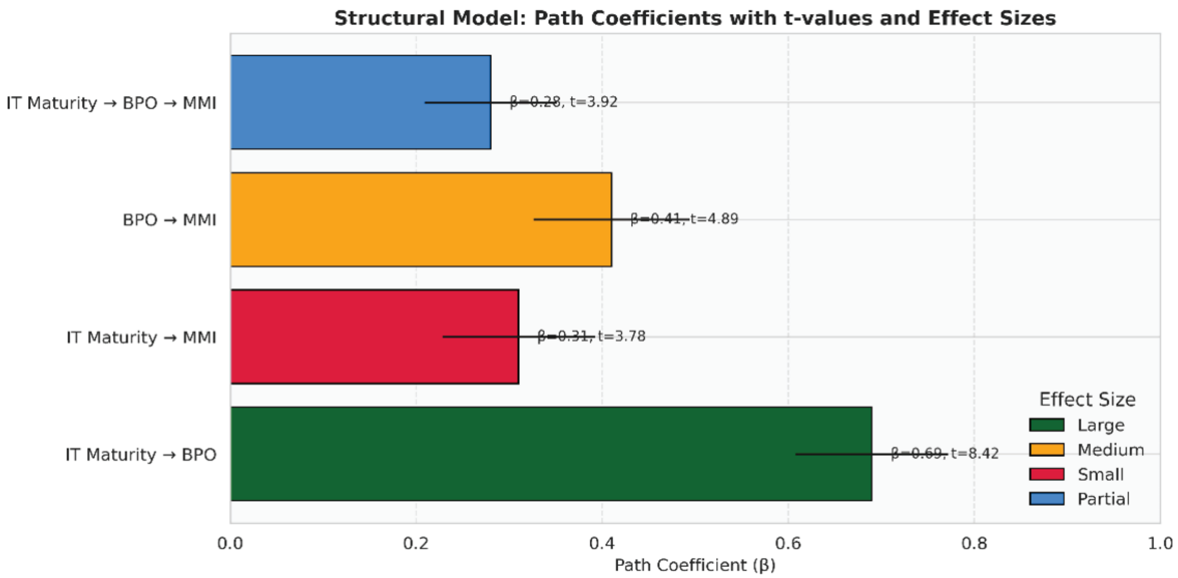

Figure 4. Path coefficients, t-values, and effect sizes from the structural model.

The plot 4, 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.

4.5 Multi-Group Analysis Results

Multi-group analysis was conducted to examine differences across industries and firm sizes. Industry-based comparisons revealed significant variation in path coefficients (Table 6, Figure 5). The effect of IT application maturity on business process optimization was strongest in manufacturing (β = 0.78) and finance (β = 0.74), and weakest in healthcare (β = 0.52). The IT application maturity–management model innovation relationship was significant in manufacturing and finance but weaker in healthcare and logistics. The BPO–MMI path remained significant across all industries, with varying magnitudes.

Table 6. 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***a (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

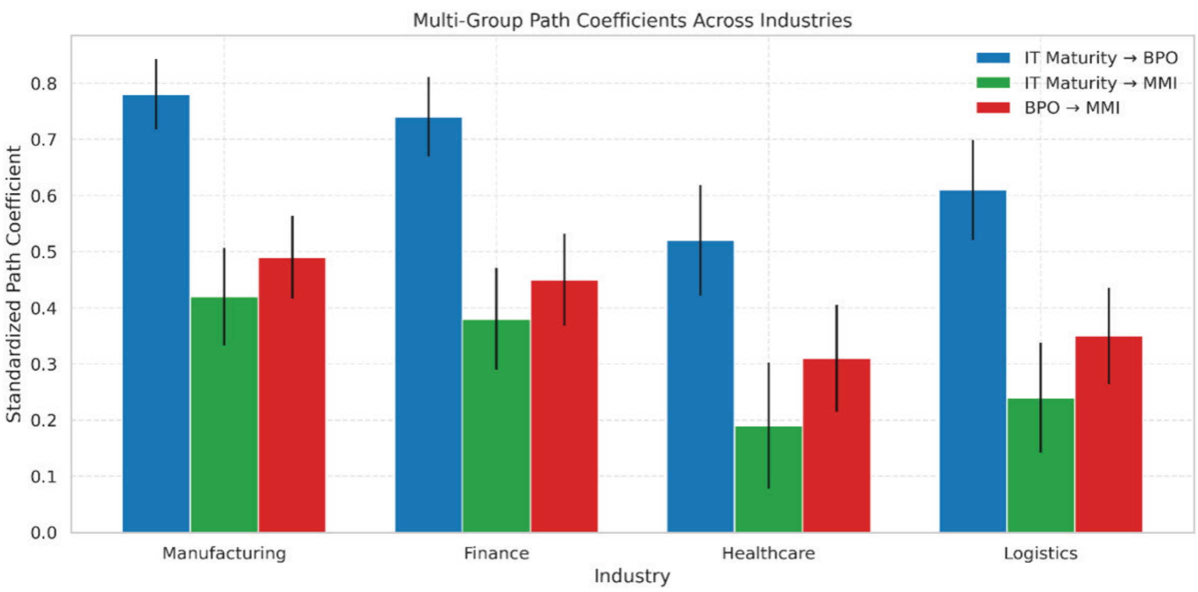

Figure 5. Bar plot comparing standardized path coefficients across four industries for IT Maturity → BPO, IT Maturity → MMI, and BPO → MMI.

This plot 5, 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

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

Predictive relevance and robustness assessments indicated satisfactory model performance. The model demonstrated substantial predictive relevance ($Q^2 > 0.25$) and acceptable predictive accuracy. Effect size analysis showed a large effect of IT application maturity on business process optimization ($f^2 = 0.89$), a small direct effect on management model innovation ($f^2 = 0.11$), and a medium effect for the BPO–MMI relationship ($f^2 = 0.20$). Detailed evaluation results are reported in Table 7.

Table 7. 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)	Cohen (1988)	Strong for BPO; Weak for MMI
	BPO → MMI	-	0.20 (Medium)	Cohen (1988)	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

4.6 Discussion

This paper has investigated the role of IT application maturity to business process optimization (BPO) and management model innovation (MMI) and whether BPO serves as the main channel through which digital capability is translated into managerial innovation. The results imply a consistent process of capability building: the more advanced the IT applications are in an organisation, the higher the probability of process optimisation, and optimised processes are linked to more powerful management model innovation. The mediation pattern also suggests that process redesign is one of the main mechanisms according to which digital transformation has become organisationally consequential, whereas a residual direct pathway suggests that digital maturity can also transform management practices even without formal process alterations.

4.6.1 Interpreting the direct effects: from digital capability to process and management change

The high correlation of the IT application maturity with BPO shows that the process level is the most immediate realization of digital maturity. This trend is conceptually aligned with the perspective that advanced IT solutions (e.g. analytics-enabled BPM, automation and combined platforms) create value in the form of stabilizing workflows, enhancing data-capture consistency, and operational frictions. In practice, digital maturity seems to operate initially as an operational intelligence enabler to make processes more visible and measurable and controllable, and then to be converted into managerial-level innovation. The direct correlation between IT application maturity and MMI is also positive, which further implies that even incomplete process redesign, mature digital infrastructures are capable of changing managerial routines. This implies that IT maturity can have a direct impact on decision architectures via expedited access to information, greater analytical visibility, and better coordination among units. In this way, managerial innovation is not a downstream effect of process improvement, but may also be produced by the managerial adoption of data-driven practices that are facilitated by fully fledged digital systems. Lastly, the positive correlation between BPO and MMI means that process optimisation is not restricted to the results of efficiency, but also connected with the adaptability of managers and organisation. With standardised and traceable processes, organisations can be in a better position to redesign governance arrangements, decentralise decision rights where it is warranted, and formalise routines that are based on reliable data. Process optimisation in this sense is a facilitating condition to management innovation since the more interpretable and usable organisational information is to decision-making, the larger.

4.6.2 Interpreting mediation: why BPO is a central mechanism

The partial mediation outcome shows that BPO is one of the key channels of transmission where IT maturity affects the management model innovation. This, in principle, justifies the claim that digital transformation can be strategically significant when it is integrated into the process structures that transform the raw data on operations into the stable, similar, and decision-relevant information. Process optimisation eliminates variability, noise, enhances measurement discipline, and the information pipeline between operations and management. This is significant since the innovation of management models needs more than the presence of data, but the availability of information that is timely, coherent, and credible to make decisions about governance and managerial practices. Simultaneously, partial mediation means that the process optimisation is not the single route to follow. Digital maturity can also directly transform management innovation by platforming enterprise wide, by providing analytics capacity or cross-functional integration which affect strategic coordination and decision speed. Thus, the results indicate that there are actually two routes: a process-mediated route (IT → BPO → MMI) and a direct managerial route (IT → MMI). This duality is conceptually significant in the sense that it separates between process-led digital transformation and decision-led transformation whilst showing that process optimisation continues to be a hegemonic process.

4.6.3 Implications for Competitive Intelligence and Strategic Decision-Making

These results give a direct evidence that digital transformation is a competitive intelligence (CI) capability-building mechanism. The high influence of the maturity of IT applications on the optimisation of business processes means that organisations that are digitally developed create better-quality operational signals and more credible streams of data, which enhances strategic sensing and lessens ambiguity in information about organisations. The favourable correlation between management model innovation and business process optimisation further contributes to the fact that intelligence is decision-relevant when the processes are standardised, traceable and analytically interpretable, which are the conditions that allow the managers to institutionalise data-driven routines, governance practices, and coordination mechanisms. In addition, the partial mediation suggests that IT maturity reinforces CI in two pathways, an indirect pathway through process optimisation (where operational data are optimised into useable intelligence) and a direct pathway through which mature IT and analytics capabilities affect managerial innovation even in the incomplete process change. All in all, the research explains the development of CI as a result of the interplay between technology capability (IT maturity), information processing structures (BPO), and decision architectures (MMI) and not as a result of a single intelligence unit. This framing is significant as it empirically sustains a capability-based channel between digital infrastructure and intelligence-enabled strategic decision-making and competitive positioning.

4.6.4 International applicability and cross-sector transferability

The empirical sample is in a range of industries, the framework proposed can be transferred as it encompasses general capability-building mechanisms that may be used in a variety of institutional settings. In knowledge-intensive industries (e.g., professional services, ICT, manufacturing based on R&D), the maturity of IT application can enable fast sensing of market and operational signals, process optimization can enable a uniform knowledge capture and comparability across units which are required to make intelligence-driven decisions. The same mechanism can reinforce the decisions on policy intelligence and resource allocation in public or hybrid organizations especially where transparency, auditability and standard workflow are fundamental.

In the global arena, the model can be duplicated in the developed as well as emerging economies. The structure facilitates responsiveness to faster sensing, processing, and decision-making in highly competitive markets because the quality of information is enhanced and the governance is in alignment. It may mitigate the informational volatility of institutionally uncertain environments, through enhancing the data traceability and process discipline, meaning it may support more stable strategic choices. The next study must measure cross-country measurement invariance and test the boundary conditions, including regulatory intensity, maturity of data governance, and environmental turbulence, which can determine the intensity of the IT -BPO-MMI pathway.

Placing the maturity of IT applications, business process optimisation and management model innovation as layers of sequential capabilities, this study advances the digital transformation research beyond the operational outcomes and offers the CI-based way of explaining how digital maturity turns into a structurally significant event. These findings suggest that one of the key processes that transforms digital capability into intelligence-ready information and managerial innovation is process optimisation, and the other direct pathway is that advanced digital systems can transform decision routines beyond process redesign. As a result, the framework provides a theoretically based and empirically validated framework that connects digital transformation to strategic sensing, intelligence processing, and decision integration, which contributes to competitive advantage in sectors and situations.

5 CONCLUSION

The results of this paper affirm that Information technology application maturity is an important factor that contributes to business process optimisation which consequently aids in the creation of management model innovation. Though, IT maturity has a moderate direct effect on managerial innovation, the main impact is achieved by enhancing the efficiency, consistency, and operational efficiency of the processes. The structural model has a high explanatory and predictive power, which is ensured by a high level of reliability, validity, and effect-size measures. Moreover, an important contextual element was the size of the firm, where bigger organisations would gain greater advantages of digital initiatives as they have better technological conditions, support of leaders, and access to resources. This study elucidates that digital transformation is not only efficient in operations but also strategic information creation and quality of decisions by viewing IT application maturity, business process optimisation, and management model innovation as consecutive levels of competitive intelligence ability. Such an ability-based view explains why digitally mature organisations display more stable competitive positioning: they are more capable of detecting the appropriate signals and transforming them into intelligible knowledge and entrenching intelligence into managerial routines and governance system.

5.1 Recommendations

Business process optimisation should be viewed as a core strategic process and not another by-product of technology adoption by organisations that want to increase their rate of innovation by means of digital transformation. The maturity of investments in IT application should be supported with structured change-management practices, active supervision of leadership, and the development of digital and analytical skills in employees in a systematic way. In the case of small and medium-sized enterprises, the internal capacity limitation can be addressed by providing specific assistance to scalable digital infrastructure and selective outsourcing of professional skills. In all sectors, the process-mining tools should be institutionalised to make it possible to monitor using evidence-based approaches, assess performance continuously, and refine transformation efforts.

5.2 Final Thoughts

This research highlight the fact that the application of technologies alone will not produce the sustainable organizational value, unless it is integrated into the streamlined processes and enhanced by the managerial willingness. When IT capabilities, process structures and decision practices develop in a coordinated fashion, then digital transformation becomes effective. Future studies can apply this framework to other national settings and use longitudinal study designs to observe changing patterns of transformation over a period. Finally, organizations that combine digital ability with process discipline and adaptive management systems have higher chances of attaining long-term innovation and competitive power in the ever-complicated surroundings.

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