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CONCEPTUAL ANALYSIS OF FACTORS AFFECTING SUCCESS IN DATA-DRIVEN BUSINESS PROCESSES: AN ARTIFICIAL INTELLIGENCE-BASED MODEL PROPOSAL

VERİYE DAYALI İŞ SÜREÇLERİNDE BAŞARIYI ETKİLEYEN FAKTÖRLERİN KAVRAMSAL ANALİZİ: YAPAY ZEKÂ TABANLI BİR MODEL ÖNERİSİ

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Abstract
In recent years, the integration of artificial intelligence (AI) into business process management (BPM) has gained significant momentum, particularly in data-driven organizational structures. This study proposes a method-based conceptual model that integrates organizational critical success factors (CSFs) with AI-enabled process management components. The model is designed to include input components such as senior management support, data governance, data quality, data literacy, and technical infrastructure. It also incorporates an AI-based process mechanism consisting of machine learning, predictive analytics, process automation, and recommendation systems. This structure is constructed to produce output variables such as decision quality, operational efficiency, process success, and agility. Adopting a feedback-driven and adaptive system logic, the model aims to develop learning-based process cycles. The model's components are structured through a comprehensive literature review covering the past five years and evaluated comparatively with cognitive BPM models and AI-enabled process frameworks. The findings indicate that aligning AI technologies with organizational readiness factors can enhance strategic decision quality and digital transformation success. This conceptual framework offers both an academic contribution and a practical roadmap for institutions that want to implement AI-supported processes.
Keywords: Artificial Intelligence, Business Process Management, Critical Success Factors, Data-Driven Decision Making, Digital Transformation

Özet
Son yıllarda, yapay zekânın (YZ) iş süreçleri yönetimine (BPM) entegrasyonu, özellikle veriye dayalı organizasyonel yapılarda önemli bir ivme kazanmıştır. Bu çalışma, organizasyonel kritik başarı faktörlerini (KBF) yapay zekâ destekli süreç yönetimi bileşenleriyle bütünleştiren, yöntem temelli kavramsal bir model önermektedir. Model; üst yönetim desteği, veri yönetişimi, veri kalitesi, veri okuryazarlığı ve teknik altyapı gibi giriş bileşenlerini içerecek şekilde tasarlanmıştır.

Ayrıca makine öğrenmesi, tahmine dayalı analiz, süreç otomasyonu ve öneri sistemlerinden oluşan YZ tabanlı bir süreç mekanizması da modele dâhil edilmiştir. Bu yapı, karar kalitesi, operasyonel verimlilik, süreç başarısı ve çeviklik gibi çıktı değişkenlerini üretmek üzere kurgulanmıştır. Geri beslemeli ve uyarlanabilir bir sistem mantığını benimseyen model, öğrenmeye dayalı süreç döngülerinin geliştirilmesini amaçlamaktadır. Modelin bileşenleri, son beş yılı kapsayan kapsamlı bir literatür taramasıyla yapılandırılmış ve bilişsel BPM modelleri ile YZ destekli süreç çerçeveleriyle karşılaştırmalı olarak değerlendirilmiştir. Bulgular, YZ teknolojilerinin organizasyonel hazırlık faktörleriyle uyumlu olarak konumlandırılmasının, stratejik karar kalitesini ve dijital dönüşüm başarısını artırabileceğini göstermektedir. Bu kavramsal çerçeve, hem akademik bir katkı sunmakta hem de YZ destekli süreçleri uygulamak isteyen kurumlar için pratik bir yol haritası niteliği taşımaktadır.
Anahtar Kelimeler: Yapay Zekâ, İş Süreçleri Yönetimi, Kritik Başarı Faktörleri, Veriye Dayalı Karar Verme, Dijital Dönüşüm

1. INTRODUCTION

In today's rapidly digitizing business world, businesses need to go beyond operational efficiency and manage their business processes as strategic resources to gain competitive advantage. Business Process Management (BPM) is an important management tool for aligning business processes with corporate goals, increasing efficiency, and ensuring sustainable customer satisfaction (Odionu et al., 2024). BPM not only streamlines operational flows, but also increases the overall agility of the organization, accelerates decision-making processes, and provides a holistic framework for achieving strategic goals by optimizing resource utilization (P. P. Sari, 2025). In this respect, it is clearly seen that BPM directly contributes to corporate success (Kerpedzhiev et al., 2021).

Digital transformation is a multifaceted process of change that requires not only the adoption of new technologies but also the reshaping of organizational structure, culture, and business models. In this process, BPM serves as a bridge that forms the infrastructure of digitalization, integrating with artificial intelligence, the Internet of Things (IoT), and smart automation technologies to both increase process efficiency and enable the delivery of innovative services (Kerpedzhiev et al., 2021; Odionu et al., 2024). In this context, BPM has evolved into a transformation tool not only at the operational level but also at the strategic level. The BPM competency framework demonstrates how digitalization requires new capabilities in process management and how existing structures must respond to this change (Kerpedzhiev et al., 2020). In recent years, AI-based technologies have significantly expanded the scope of BPM applications. Functions such as real-time monitoring of process data, anomaly detection, automated decision-making, and predictive analysis have become possible through the integration of AI into processes. The importance of data-driven decision support systems for autonomous process management is particularly emphasized (Saleem et al., 2020). More proactive process management models emerge thanks to the combination of algorithmic predictions with managerial reflexes (Provost & Fawcett, 2013). These developments have brought about not only technical but also managerial paradigm shifts. At the heart of this transformation is a culture of data-driven decision-making. The ability of organizations to manage processes not only with past performance data but also with future scenarios improves decision quality at every level, from strategic planning to operational actions. It is stated that analytical systems directly impact process success (Biernikowicz et al., 2025). Data culture has become a fundamental basis for business decision-making processes (Provost & Fawcett, 2013). In this context, data analytics and artificial intelligence applications are integrated with BPM structures, enabling not only the monitoring of processes but also their strategic direction.

While the existing literature comprehensively demonstrates how BPM has been redefined in the context of digitalization, studies that systematically address the factors affecting process success at a conceptual level and relate these factors to an AI-based model are quite limited (Kerpedzhiev et al., 2020). While applied BPM models have been widely developed, their theoretical foundations are often incomplete or focused solely on technical outcomes. Therefore, there is a need in the literature for studies that analyze the factors determining process performance with a multidimensional approach and propose a conceptual framework supported by artificial intelligence.

This study aims to conceptually analyze the factors affecting the success of data-driven business processes and, based on this analysis, propose an AI-based model. Going beyond similar studies in the literature, the study offers an approach that holistically addresses not only technological implementation recommendations but also the structural, cultural, and managerial factors that influence process success. Furthermore, the proposed model's reliance on explainable AI principles makes it not only a results-oriented but also an interpretable and extensible decision-support tool. In this respect, the study contributes to the theoretical literature and presents a unique framework that can guide businesses undergoing digital transformation.

2. CONCEPTUAL FRAMEWORK AND LITERATURE REVIEW

In today's digital economy, businesses' ability to achieve sustainable competitive advantage depends not only on their effectiveness in delivering products or services, but also on the management of the business processes that produce these outcomes. In this context, Business Process Management (BPM) facilitates the modeling, monitoring, execution, and continuous improvement of processes, contributing to the establishment of a strong link between organizations' strategic goals and process implementations (Butt, 2020). Especially with Industry 4.0 and digital transformation, BPM has become not only an operational tool but also a structure that forms the governance basis of digitalization (Labus et al., 2020). Effectively implementing BPM in a corporate context requires the development of specific organizational competencies. In this context, strategic alignment, process governance, technology integration, the role of human resources, and organizational culture stand out as critical components for successful process implementation (Antonucci et al., 2020). BPM competency models, which are widely used in the literature, provide a systematic structure for these components, making it possible to both manage processes in a digital environment and support organizational transformation.

The digitalization process is reshaping not only the use of technological tools but also the way organizations make decisions, configure resources, and create value. Within this transformation, the concept of "capability sourcing" requires businesses to focus not only on their existing resources but also on strategic capabilities that can be acquired from external sources. Rafati and Poels (2014), argue that capability sourcing is not merely an operational decision aimed at cost reduction but also a strategic component of organizational value creation. Crucial to this approach is the acquisition of the right competence from the right source, at the right cost, and in the right geographic location, thus integrating it into the organizational structure. Making sound capability sourcing decisions requires thinking at a high level of abstraction and expressing this thinking through conceptual models. In this context, he argues that conceptual modeling techniques based on service-oriented logic facilitate strategic governance processes by creating a common language among decision-makers. This modeling approach supports more robust decisions about how organizational capabilities can be structured through internal resources (insourcing), external resources (outsourcing), or business partnerships (co-sourcing). Another approach compatible with the conceptual foundations of BPM is the LBU (Logical Business Unit) model developed by Turner et al. (2004). This model defines the life cycle of business units and recommends considering processes not only in terms of functional outputs but also from a value creation perspective.

This allows for clearer monitoring of the dynamic positions of processes within the organization, and strategic restructuring of these processes can be achieved.

In line with this theoretical framework, this study aims to systematically conceptualize the factors affecting the success of business processes within the framework of digital transformation and a data-driven decision-making culture, and to integrate these factors into an AI-supported model proposal. Unlike other studies, this approach proposes not only a technical solution but also a holistic framework encompassing decision support, explainability, and strategic alignment. Thus, the proposed model not only contributes theoretically to the BPM literature but also provides a unique conceptual foundation that can guide the strategic orientations of businesses during the digital transformation process.

A study conducted by Daradkeh et al. (2021) on data-driven decision-making processes in businesses examines the impact of big data analytics on business decision-making processes. The study examined the impact of big data technologies on factors such as organizational agility, customer relationship management, operational efficiency, and innovation. Data obtained from medium- and large-scale businesses in Jordan were analyzed. The findings revealed that the use of big data analytics improves the competitiveness of businesses, particularly by increasing decision-making speed and accuracy. Duan et al. (2020) explored the impact of AI technologies on business decision-making processes using an empirical survey. The study was conducted using 218 valid responses from organizations across various sectors. The findings indicate that AI applications improve decision-making quality, reduce uncertainty, and strengthen managerial decision-making reflexes. The most widely used AI technologies include machine learning, natural language processing, and expert systems. They also noted that factors such as data quality, organizational structure, technology adoption, and management support are decisive in the success of AI-based decision systems. In another study, Chaudhuri et al. (2021) examined how big data analytics applications are evaluated in decision-making processes. The study noted that big data helps businesses make faster and more accurate decisions in the face of environmental uncertainty and strengthens their strategic orientation capacity. Data management infrastructure, analytical competence, and an organizational learning culture stand out as influential factors in the success of big data projects. A study conducted by Hussinki (2022) explores the relationship between business analytics and firm performance. The study analyzed 47 peer-reviewed empirical studies published between 2000 and 2022. The literature was integrated to encompass subfields such as big data analytics, data analytics, business intelligence, and business analytics. The findings suggest that business analytics competence encompasses not only data and technology-based resources but also technical skills, managerial capabilities, and a data-driven cultural structure. Another study by Saleem et al. (2020) found that the use of big data does not have a statistically significant direct impact on firm performance, but this relationship is indirectly established through product and process innovations. It also emphasized that knowledge sharing has a strengthening effect on the relationship between big data and innovation. Overall, these studies demonstrate that data-based technologies should be considered not merely as technical tools but as strategic components integrated into organizational structures.

2.1. Business Process Management (BPM) and Digital Transformation

Business Process Management (BPM) is a comprehensive management approach based on the definition, execution, monitoring, and continuous improvement of processes to achieve organizational goals. This approach aims not only to increase operational efficiency but also to generate corporate value through processes, foster agility, and ensure strategic alignment. With the increasing impact of digital transformation on business practices, BPM has moved beyond being merely a technical process tool and has begun to play a central role in organizations' digital transformation strategies (Antonucci et al., 2020; Enriquez et al., 2020).

Digital transformation is a multifaceted process of change that requires businesses to restructure their business models, organizational structures, and decision-making systems. This transformation is not limited to simply updating technological infrastructure; it also includes restructuring process architecture, integrating data-based decision support systems, and adopting a flexible governance approach. In this context, BPM has become a framework that encompasses not only the technical but also the strategic and cultural dimensions of digital transformation (Broccardo et al., 2023; Hadysah & Pratama). The success of BPM in the digital transformation process depends not only on the automation or digitization of processes but also on the extent to which the organization internalizes this change. Organizational culture, in particular, is a decisive factor in the dissemination and sustainability of process management throughout the organization. Organizations' capacity to embrace and own processes and foster a culture of continuous improvement determines the long-term impact of BPM. Therefore, cultural structure should be considered a central component that cannot be overlooked in BPM implementations (Antonucci et al., 2020; Saravia-Vergara et al., 2020). However, technological advancements also play a significant role in the digital reshaping of BPM. Advanced technologies such as artificial intelligence, machine learning, and data analytics, in particular, strengthen BPM's predictive capabilities and make decision-making processes more data-driven. The proliferation of low-code platforms makes BPM applications more accessible and flexible, allowing users without technical knowledge to contribute to process automation. This democratizes process management and fosters a more participatory structure across the organization (Enriquez et al., 2020; Kalluri, 2023).

The integration of data-driven decision-making capabilities into process management further enhances the strategic value of BPM. Real-time data monitoring, process performance analysis, and predictive scenarios enable faster and more reliable process decisions. Data-driven BPM structures offer significant advantages to businesses, particularly in reducing uncertainty in complex business processes and supporting continuous improvement cycles. In this context, achieving digital maturity requires not only advanced technical infrastructure but also advanced decision support systems (Distel et al., 2023; Rahman, 2024). In this transformation process, BPM is becoming not just a management tool but also a fundamental component driving an organization's digital strategy. Structuring processes, supporting them with digital technologies, integrating them into culture, and integrating them with data-based decision systems enhances BPM's transformational power and directly contributes to corporate sustainability. Therefore, in digitalizing businesses, BPM is positioned not only as a structure that manages past process data but also shapes the competitive strategies of the future.

2.2. Data-Driven Decision Making and Artificial Intelligence Integration

Data-based decision-making processes allow organizations to make more rational and accurate decisions by systematically analyzing high-volume and diverse data (Mahmoud et al., 2020). This approach not only reacts to past performance but also provides an effective basis for creating future decision scenarios (Anica-Popa et al., 2023). In this process, big data analytics reduces managerial uncertainties by increasing decision speed and supporting insight generation (Eyitayo et al., 2024; Mahmoud et al., 2020). The information density and versatile analysis capacity provided by systems supported by big data analytics play a decisive role in increasing decision quality (Anica-Popa et al., 2023). Through these systems, managers can extract meaningful patterns from data and achieve more strategic and consistent results (Mahmoud et al., 2020). A data-driven decision-making culture not only enhances the competence of decision makers but also embeds knowledge-based thinking throughout the organization (Awan et al., 2021; Lu et al., 2020). Artificial intelligence applications make decision support systems more effective through automation of data analysis processes and reduce the need for human intervention (Zebec & Indihar Štemberger, 2024). These technologies increase speed and accuracy while ensuring repeatability and traceability of decision processes (Lu et al., 2020; Mahmoud et al., 2020).

In addition, artificial intelligence-based automations that provide performance improvements at the process level help make timely and accurate decisions (Zebec & Indihar Štemberger, 2024). This technological transformation enables businesses not only to analyze existing data but also to create scenarios about future trends through predictive modeling (Lu et al., 2020). In this context, data processing processes are evolving from descriptive analysis to predictive and advanced predictive systems. Developing organizations' decision support infrastructures in this direction directly contributes to increased process maturity and decision accuracy (Eyitayo et al., 2024; Lu et al., 2020).

Current developments make it possible not only to resolve unforeseen situations in decision-making processes, but also to optimize forward-looking strategic moves (Eyitayo et al., 2024). In particular, the integration of advanced analytical techniques – such as predictive modeling, machine learning, and visual analysis – into decision support processes makes it easier for organizations to respond more flexibly and proactively to environmental variables (Lu et al., 2020). Data science, in this context, encompasses not only analysis but also visualization and meaning-making processes within an organizational context. Visual analytics tools provide decision-makers with simplified and effective information, supporting the rapid translation of insights into action (Lu et al., 2020). These structures, which work integrated with business intelligence systems, contribute to the resource optimization of small and medium-sized enterprises in particular (Eyitayo et al., 2024). Despite all these advantages, effective data-driven decision-making systems require sufficient organizational infrastructure and data management maturity. Factors such as data quality, accessibility, reliability, and analyzability directly impact the success of decision-making processes (Anica-Popa et al., 2023). In addition to technical compatibility, social factors such as user acceptance, ethical responsibilities, and explainability should also be taken into account when integrating artificial intelligence systems into decision-making processes (Eyitayo et al., 2024). The integration of data-driven decision-making systems and artificial intelligence technologies stands out as a strategic transformation that is reshaping decision processes in the modern business world. This integration makes process management more measurable, flexible, and predictable, and organizations can be more resilient in the face of uncertainty (Eyitayo et al., 2024; Zebec & Indihar Štemberger, 2024).

2.3. Factors Affecting Data-Driven Process Success

The success of data-driven business processes depends not only on the implementation of technological solutions, but also on the holistic integration of organizational structure, cultural alignment, and managerial commitment. These conditions are frequently described in the literature as critical success factors (CSFs) and form the foundation for the sustainability of AI-based process management (Mahmoud et al., 2020; Sleep et al., 2019; Storm & Borgman, 2020). In this context, one of the most significant factors is senior management support. Senior executives' leadership in strategic decisions, their ability to disseminate a data-driven transformation vision throughout the organization, and their ability to drive cultural change directly impact process ownership (Antonucci et al., 2020; Storm & Borgman, 2020). This support ensures the continuity of technological investments not only at the purchasing level but also in the process integration and internalization stages (Eyitayo et al., 2024).

Data governance is also crucial for process reliability. Elements such as data security, access control, privacy, transparency, and compliance are crucial, especially in the management of big data and artificial intelligence systems (Decker, 2019; Sadykova, 2020). This factor is not just about structuring technical systems; it is also about governance principles that clarify ownership and corporate responsibility for data within the organization (Broccardo et al., 2023).

Data quality and integration are key factors affecting the accuracy of data-driven decision-making mechanisms. For decision support systems to function effectively, data must be clean, up-to-date, integrated, and analyzable (Pikkarainen et al., 2020; Sleep et al., 2019).

Failure of data integration directly undermines the reliability and output quality of AI systems (Mahmoud et al., 2020; Zebec & Indihar Štemberger, 2024). Another important factor is employees' level of data literacy. Understanding, interpreting, and effectively using data in decision-making processes requires that all employees, not just technical teams, possess this competency (Awan et al., 2021; Sadykova, 2020). Therefore, the development of analytical competencies and continuous training programs for employees are variables that directly affect success (Lu et al., 2020). Cultural alignment and openness to change within the organization are among the social factors that determine the success of data-driven transformation projects. Resistance to change can delay the adoption of new systems and undermine employee engagement (Sleep et al., 2019). To prevent this, organizations need to internalize a culture of open communication, participation and learning (Decker, 2019; Saravia-Vergara et al., 2020). Communication strategies and change management plans are also among the success factors. The meaning, purpose, and function of data-driven transformation must be transparently communicated throughout the organization (Eyitayo et al., 2024). Thanks to this communication, it can be clearly stated why the transformation is necessary and what contributions it will make to employees (Anica-Popa et al., 2023). Infrastructure and technology investments form the technical foundation of the process. Successful deployment of artificial intelligence infrastructures, big data processing engines, and business intelligence systems plays a critical role in process automation and real-time decision support (Lu et al., 2020; Zebec & Indihar Štemberger, 2024). However, as well as the adequacy of the technological infrastructure, the human resources that will manage these systems must also have advanced analytical skills (Mahmoud et al., 2020; Sadykova, 2020). Competency development and training policies directly increase an organization's capacity for informed decision-making. Such investments enable the institutionalization of a data culture and the integration of employees with new technologies (Awan et al., 2021; Storm & Borgman, 2020). Finally, clarity of organizational structure and process ownership is a key structural factor determining success. Issues such as who runs the processes, who is responsible for which data, and at what level decisions are made must be clearly defined (Broccardo et al., 2023; Pikkarainen et al., 2020). Furthermore, encouraging a culture based on trial and error and learning makes it easier for data-based decision-making mechanisms to become permanent (Decker, 2019; Storm & Borgman, 2020). In conclusion, the factors affecting the success of data-driven processes are not limited to investments in technology. Many factors, such as senior management support, data governance, cultural alignment, technical infrastructure, employee competence, and organizational structure, must be addressed together. A healthy structuring of these factors will also directly support the functionality of the proposed AI-based model.

3. DEVELOPMENT AND PROPOSAL OF AN ARTIFICIAL INTELLIGENCE-BASED CONCEPTUAL MODEL

This study is a theoretically grounded study that aims to propose an AI-based model by analyzing the conceptual elements that influence success in data-driven business processes. A qualitative research approach was adopted to develop a conceptual model. In the literature, studies on the integration of AI into process management focus primarily on technical applications; modeling on how organizational factors can be integrated into this structure remains limited (Gînguță et al., 2023; Rana, 2024). Therefore, the proposed model aims to provide a conceptual framework that integrates success factors and AI-enabled process components. The model was developed based on academic studies on the integration of AI applications into business processes, organizational success factors in digital transformation, and data-driven decision-making processes. Literature searches were conducted using databases such as Google Scholar, Web of Science, and Scopus, based on scientific articles published in recent years.

These studies emphasize that factors such as technical infrastructure, senior management support, data quality, and data literacy affect process success (Mahmoud et al., 2020; Oluwatoyin Ajoke et al., 2023; Storm & Borgman, 2020). Furthermore, it is stated that technologies such as artificial intelligence-based automation, recommendation systems, and predictive analysis have the potential to improve process decisions and organizational agility (Gînguță et al., 2023; Rana, 2024). By integrating these conceptual structures, a flexible and feedback-based model that is responsive to process dynamics has been constructed.

3.1. Structure and Components of the Model

The model consists of three fundamental structures: input components, process mechanism, and output components. In addition to strategic factors such as "Top Management Support," "Data Governance," and "Data Quality," the input components also include "Data Literacy" and "Technical Infrastructure," which directly support these elements. These factors have been considered in the literature as critical organizational conditions for data-driven process success and digital transformation capacity (Mahmoud et al., 2020; Oluwatoyin Ajoke et al., 2023; Storm & Borgman, 2020). This structure provides a holistic assessment not only of system implementation but also of individual competence and the organizational culture's openness to technology. Data governance and literacy, in particular, are fundamental prerequisites for the healthy integration of AI applications into business processes. Process components encompass four core technological capabilities under the heading "AI-Enabled Process Management": machine learning, predictive analytics, process automation, and recommendation systems (Rana, 2024; Zebec & Indihar Štemberger, 2024). These AI tools enable not only data analysis but also decision-making, process optimization, and scenario development. This level of process engine sophistication transforms the system from a passive to an action-oriented structure. In other words, processes are no longer solely operational but also focused on learning and development.

The resulting components are the measurable outcomes of organizational success: indicators such as "Process Success," "Decision Quality," "Operational Efficiency," and "Agility" reflect not only technical success but also levels of strategic and agile alignment (Anica-Popa et al., 2023). These outcomes serve as conceptual foundations for testing the model's validity and are among the evaluation criteria for managerial performance. Indicators such as agility and decision quality, in particular, demonstrate the sustainability of the value derived from AI. The layered structure of the proposed AI-based conceptual model and its interactions between processes are systematically presented in Figure 1.

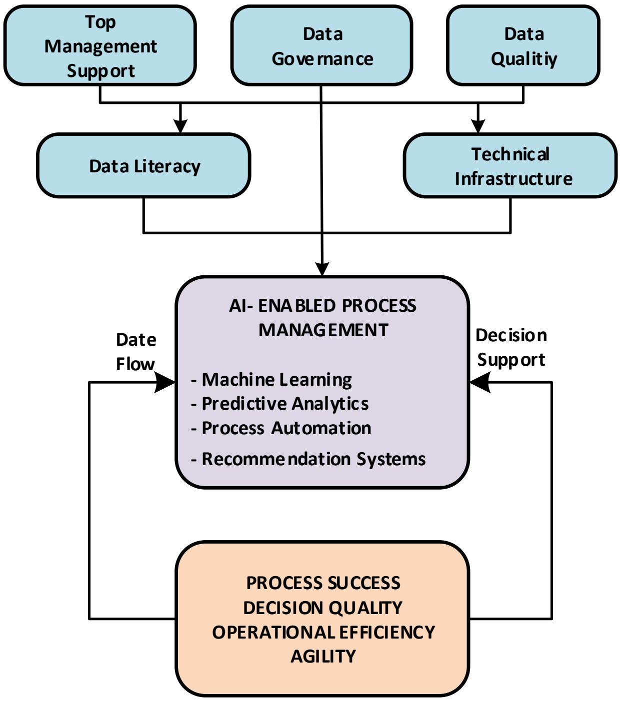

Figure 1. Artificial Intelligence-Based Conceptual Model Proposal

The model has a multi-component structure, starting with organizational success factors, progressing to AI-supported process management, and ultimately to a system structure that learns from process outputs. The input → process → output → feedback loop reflects the model's dynamic nature. This structure provides a guiding framework not only for improving existing processes but also for designing new ones.

The top layer of the model, "Top Management Support," "Data Governance," and "Data Quality," represents the level of institutional readiness and managerial commitment. These factors have been cited in the literature as prerequisites for the effective operation of AI systems (Mahmoud et al., 2020; Storm & Borgman, 2020). This tripartite structure facilitates institutional ownership and sustainability of decisions, rather than directly impacting the success of technological processes. AI gains meaning not only through algorithms but also through such institutional support mechanisms. Top management support, in particular, ensures that the strategic vision progresses in harmony with technology. In environments where management lacks ownership of these processes, even the most advanced technologies fail to deliver the expected impact.

The "Data Literacy" and "Technical Infrastructure" components in the second layer connect input factors to the process. Data literacy enables employees to effectively participate in data-based decision-making processes, while technical infrastructure enables the smooth operation of systems (Oluwatoyin Ajoke et al., 2023; Rana, 2024). While these two factors may appear technical, they actually represent critical points of human-system interaction. What's striking here is that human capital is equally important as technological hardware in this structure. A business may use the best software, but if employees can't analyze data, the system becomes ineffective. Therefore, the model adopts an approach that integrates technology with people. The "AI-Enabled Process Management" block, located at the center of the model, represents business processes reengineered with artificial intelligence. The components listed in this area machine learning, predictive analytics, process automation, and recommendation systems are among the priority technologies for digital process maturity in the current literature (Gînguță et al., 2023; Zebec & Indihar Štemberger, 2024). These technologies provide multifaceted contributions, including not only data processing but also decision support, developing alternative scenarios, and adding agility to operational processes.

In this respect, the model is based on an active AI infrastructure that not only analyzes data but also guides decision-making processes. This allows organizations to not only monitor the past but also develop strategic scenarios for the future.

The subsections titled "Process Success," "Decision Quality," "Operational Efficiency," and "Agility" are the outputs of the model. These indicators relate not only to the proper functioning of the process but also to concepts such as organizational learning, strategic orientation, and sustainable competitive advantage (Szelągowski & Lupeikiene, 2020). While increased decision quality ensures managerial consistency, agility represents organizations' ability to adapt to rapid change. These outputs are not merely the return on a technological investment but also the transformation of organizational competence. Businesses should consider these outputs not only as performance indicators but also as strategic parameters measuring competitiveness. The arrows surrounding the model, marked with "Data Flow" and "Decision Support" in the visual, illustrate the feedback relationship and the learning nature of the system. Thanks to this structure, the model operates in a cyclical, rather than linear, manner. Each process output carries the potential to shape subsequent stages of the system. With this approach, organizations can both learn from the past and shape the future (Eyitayo et al., 2024). Such feedback-based systems are particularly preferred in digital transformation strategies because they offer a living system design rather than a fixed structure.

4. CONCLUSION AND DISCUSSION

This study proposes an AI-based conceptual model based on an analysis of the factors affecting success in data-driven business processes. The model develops a unique structure by integrating organizational success factors frequently emphasized in the literature (e.g., senior management support, data governance, data quality, technical infrastructure, and data literacy) with AI-based process mechanisms. Designed based on an input-process-output logic, the model places AI technologies at the core of the process with functions such as decision support, process automation, predictive analysis, and recommendation systems. Outputs such as decision quality, operational efficiency, agility, and process success are positioned as the outcome components of the model. The study's most significant contribution is its conceptualization of AI beyond a technical tool, in relation to the dynamics of organizational success. This provides a holistic framework for how AI-enabled processes can be structured not only technologically but also at organizational and strategic levels. The model's feedback mechanism transforms it from a solely descriptive framework to a learning and evolving systems logic. Thus, the model provides a unique theoretical contribution to both the process management literature and the integration of digital transformation and artificial intelligence.

In recent years, the AI-based transformation in business process management (BPM) has been studied in the literature using various conceptual models. A comparative evaluation of the model proposed in this study against existing approaches is crucial for revealing its innovative aspects.

The Cognitive BPM approach proposed by Hildebrand et al. (2024) envisions refining through cognitive capabilities, rather than being limited to extensive automation. The authors recommend integrating decision support information with artificial intelligence software and incorporating elements of continuous learning and adaptation. The process monitoring, predictive analysis, and recommendation systems components included in this logical, proposed model share structural parallels with the concepts of "cognitive decision support" and "cognitive process learning" emphasized in Hildebrand's model. Dumas et al. (2023) propose the AI-Augmented Business Process Management Systems (ABPMS) approach, advocating for the development of framework-based, self-explanatory, and adaptive systems beyond traditional BPM systems. The ABPMS model defines the functionality of AI in process management in a layered manner by dividing the process lifecycle into stages such as "frame-perceive-reason-enact-explain-adapt-improve."

In this respect, the feedback loop in the model presented in our study conceptually reflects Dumas's "explain" and "improve" stages. Weinzierl (2024) emphasizes that proactive decision-making mechanisms underlie process success in increasing AI-supported automation in BPM systems. In this approach, the collection of high-quality data and ensuring its governance are important prerequisites. This situation directly aligns with the "data governance" and "data quality" components in the proposed model. Finally, Kampik (2024) highlights the impact of explainability and trust dimensions on process success in human-machine interaction in cognitive systems. The "communicative and context-sensitive" system requirement emphasized in the study reinforces the association of the decision support systems in this study with interpretable and strategic outcomes. This demonstrates that the model is not only technical but also integrated with organizational decision structures.

Based on these comparisons, it can be argued that the proposed model, in addition to its overlap with conceptual structures in the literature, offers a more comprehensive and practical framework, particularly through its integration with organizational components such as success factors. The model enables the assessment of not only the technical architecture but also the organization's AI readiness.

The AI-based conceptual model developed in this study offers a valuable framework, particularly for organizations undergoing digital transformation, as it holistically addresses both organizational success factors and process-oriented AI applications. In this regard, some strategic recommendations for practitioners are listed below:

- *Investments should be made in data quality and data governance:* These elements, which are among the input components in the model, are prerequisites for AI systems to establish accurate learning structures. Without ensuring the consistency, integrity, and openness of process data, AI systems may not produce the expected outputs.
- *Active participation of senior management should be ensured:* As emphasized in the literature, senior management support is critical for fostering ownership of digital transformation. Without managerial commitment, AI projects can remain superficial.
- *Employees' data literacy levels should be increased:* Developing organizational capabilities is crucial for the effective use of AI-based processes not only by technical units but also by decision-makers and operational units.
- *The applicability of the model should be tested primarily through pilot projects*: The suitability of the conceptual structure for the organizational context should be assessed by applying it to small-scale processes. This allows for both feedback and facilitates adaptation processes.
- *Future research should focus on empirically testing this model*: In particular, the relationships between the model's components can be tested through structural equation modeling (SEM), case studies, and longitudinal analyses. Furthermore, applicability comparisons across different sectors can be made.

The conceptual model developed based on these recommendations can be considered not only a theoretical contribution but also a guiding tool for organizations seeking to digitize their processes. The level of institutional readiness and technological capacity will be decisive in the successful implementation of this model.

This study proposes an original conceptual model that combines data-driven decision-making processes with organizational success factors, taking into account current trends in the literature on business process management and artificial intelligence integration. With the logical connections established between input, process, and output components, the model contributes to the digital transformation processes of organizational structures and significantly overlaps with existing conceptual models in the literature. The proposed framework develops a holistic perspective that considers not only technological transformation but also human-centered components such as corporate culture, leadership support, and employee competence.

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