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Artificial Intelligence–Driven Enterprise Decision Support Systems: A Framework for Intelligent Business Process Automation in Digital Economies

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Abstract
This study investigates the growing problem that many organizations deploy artificial intelligence, analytics, and workflow automation in fragmented ways, limiting their ability to convert decision intelligence into coordinated business process automation in digital economies. The purpose of the research was to examine how AI-driven enterprise decision support systems improve intelligent business process automation and related operational outcomes. Using a quantitative, cross-sectional, case-based design, the study collected primary data through structured questionnaires from 312 valid respondents drawn from enterprise cases operating in digitally enabled organizational environments with direct exposure to AI-supported decision and automation systems. The major variables included AI-driven decision support capability, AI-enabled analytics, automation intelligence, enterprise automation readiness, and intelligent business process automation, with outcome dimensions covering business process efficiency, decision quality, organizational responsiveness, and productivity. Data were analyzed using descriptive statistics, Cronbach's alpha, Pearson correlation, and multiple regression in SPSS. The findings showed strong positive perceptions across the core constructs, with mean scores of 4.08 for AI-driven decision support capability, 4.02 for AI-enabled analytics, 3.96 for automation intelligence, 3.89 for enterprise automation readiness, and 4.11 for intelligent business process automation. Decision quality recorded the highest outcome mean at 4.19, followed by business process efficiency at 4.14, productivity at 4.06, and organizational responsiveness at 4.05. Reliability was strong, with Cronbach's alpha ranging from 0.81 to 0.90. Correlation results indicated significant positive relationships with intelligent business process automation, including AI-driven decision support capability ($r = 0.71$), AI-enabled analytics ($r = 0.67$), automation intelligence ($r = 0.69$), and enterprise automation readiness ($r = 0.63$). The regression model explained 64% of the variance in intelligent business process automation ($R^2 = 0.64$, $F = 108.42$, $p < .001$), while AI-driven decision support capability ($\beta = 0.29$), automation intelligence ($\beta = 0.26$), AI-enabled analytics ($\beta = 0.21$), and readiness ($\beta = 0.18$) significantly predicted the outcome; the moderation effect was also significant ($\beta = 0.12$, $p = .004$). The study implies that enterprises achieve stronger automation performance when AI capability is aligned with readiness, data quality, and system integration.

Keywords
Artificial Intelligence, Enterprise Decision Support Systems, Business Process Automation, Digital Economies, Enterprise Automation Readiness;

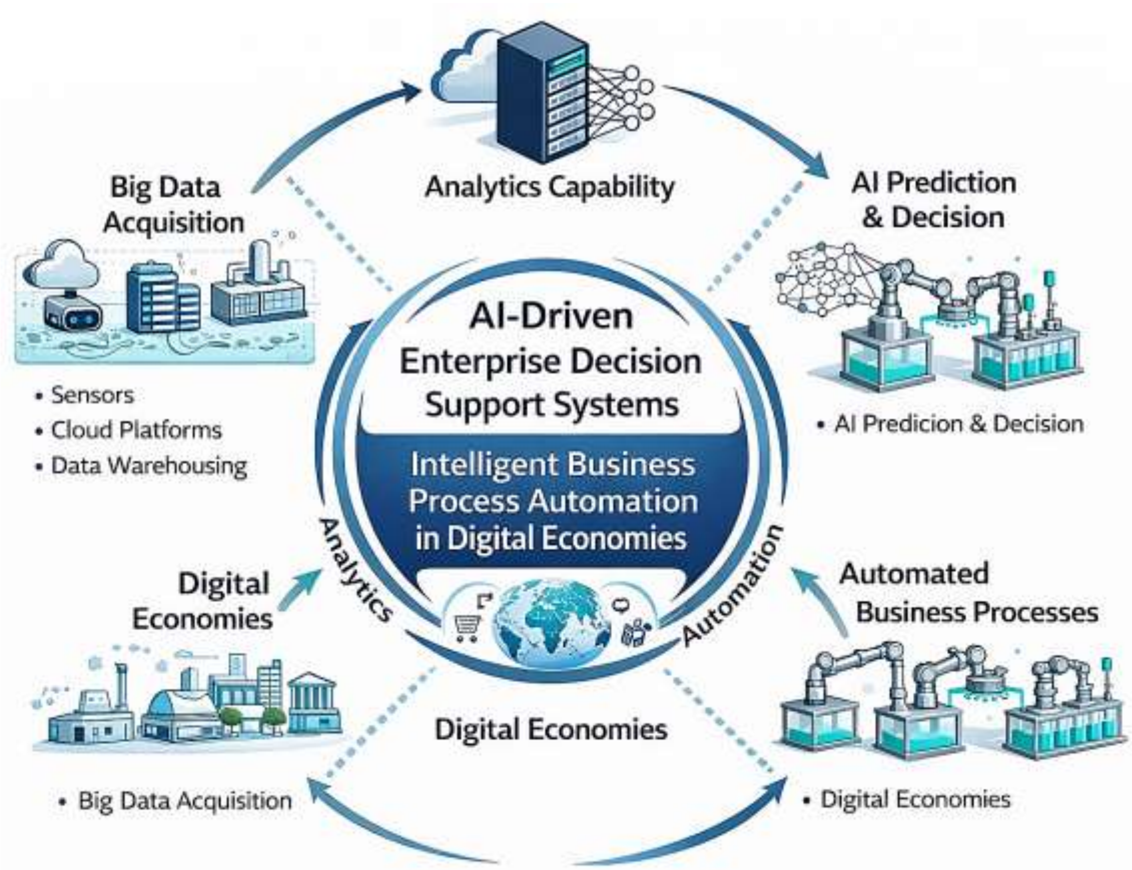
INTRODUCTION

Artificial intelligence (AI) is commonly understood in the management and information-systems literature as a family of computational techniques that perform tasks associated with learning, inference, prediction, classification, optimization, and pattern recognition, while decision support systems (DSS) are information systems designed to assist managerial judgment through data, models, and analytical logic (Chen et al., 2012). In enterprise settings, these two domains increasingly intersect, producing AI-driven DSS that combine data infrastructures, algorithmic analytics, and organizational workflows to support operational, tactical, and strategic decisions. Business process automation refers to the use of digital systems to execute, coordinate, monitor, and optimize recurring organizational activities, and in digital economies this automation is embedded in broader configurations of data platforms, cloud services, process intelligence, enterprise applications, and cross-border digital transactions (Chiang et al., 2018). The international significance of these concepts rests on the fact that firms across manufacturing, retail, logistics, banking, healthcare, telecommunications, and public services now compete through their capacity to transform data into timely action, standardize complex routines, and coordinate decisions across geographically dispersed operations. Foundational DSS scholarship established managerial decision support as a central information-systems concern, while later BI&A research expanded the field toward large-scale analytics, unstructured data, and organizational impact (Schmitt, 2023). Dynamic capabilities research added a complementary explanation by describing how firms sense opportunities, seize them through resource orchestration, and reconfigure assets under changing environments, a logic that aligns closely with AI-enabled enterprise adaptation. More recent work on digital transformation and AI in business has placed decision support, automation, and data capability at the core of contemporary enterprise restructuring, showing that AI is not simply a technical artifact but part of a wider organizational architecture that shapes routines, knowledge flows, and performance configurations. For this reason, a study of AI-driven enterprise decision support systems in digital economies begins not from a narrow software definition but from a broader understanding of how firms construct intelligent infrastructures for coordinating analysis, action, and process execution across international markets, supply chains, and digitally mediated ecosystems (Su et al., 2022).

The movement from traditional DSS to contemporary AI-driven enterprise decision support systems reflects a substantial broadening in both data logic and organizational function. Early DSS work focused on supporting bounded managerial problems through interactive models and structured information, whereas BI&A scholarship brought attention to data warehousing, text sources, web data, large-scale integration, and multi-layered analytics for decision environments characterized by higher speed and complexity. Later analyses showed that BI&A did not replace DSS so much as deepen and extend it; business intelligence, analytics, and decision support became intertwined around the common objective of converting more data into more meaningful insight for action. This transition is especially important for enterprises operating in digital economies because managerial judgment is now shaped by streaming transactions, platform interactions, customer traces, sensor data, partner-network information, and internal process records that exceed the representational limits of traditional reporting systems (Teece, 2007). Analytics capability has therefore been positioned not as a single tool but as a bundle of organizational, technological, and human resources, while evidence has shown that analytics capability relates to firm performance through process-oriented dynamic capabilities and broader organizational use. Such findings matter for enterprise DSS because AI-driven support systems depend on exactly this conversion chain: data acquisition, model development, interpretation, embedded process use, and managerial uptake. In that sense, AI-driven DSS represents a mature phase in the DSS tradition where predictive and prescriptive functions are incorporated into enterprise decision routines, not only into isolated analytical tasks (Côrte-Real et al., 2017). The literature also identifies an important conceptual shift from retrospective reporting to anticipatory and adaptive decision support, with AI models extending organizational capacity to classify risk, forecast demand, allocate resources, detect anomalies, and prioritize interventions under conditions of scale and uncertainty. This synthesis places enterprise AI-driven DSS within a long scholarly trajectory rather than treating it as a detached technological novelty.

A central theme in the literature is that AI-driven decision support gains organizational relevance when analytics capability becomes embedded in enterprise structures, routines, and performance systems. Big data analytics studies repeatedly show that value creation is mediated by organizational readiness, managerial interpretation, and integration with business processes rather than by data volume alone (Plekhanov et al., 2023). Analytics capability has been described as a configuration of tangible resources, human skills, and intangible assets, and research has linked these capabilities to firm performance through dynamic capabilities and business-value creation mechanisms. Related scholarship has emphasized the strategic value of big data and business analytics by locating analytics within broader value-creation mechanisms, while AI integration has been treated as a sociotechnical organizational process rather than a purely computational one. Research published in the early 2020s continued this line by examining mediating mechanisms such as dual innovation, data-driven culture, and management capability (Arnott & Pervan, 2014).

Figure 1: AI-Driven Enterprise DSS Framework for Intelligent Business Process Automation



Evidence has shown that big data analytics capabilities support organizational performance through exploitative and explorative innovation, while the mediating role of data-driven culture has also been documented in the relationship between big data analytics management capability and both operational and financial performance. Such evidence is directly relevant to the study of AI-driven enterprise decision support systems because enterprise DSS must translate analytical outputs into accepted, repeatable, and governable organizational action (Ahmed & Hasan, 2021; Md & Mehedi, 2021). AI models can produce classifications, forecasts, optimization outputs, and risk alerts, yet the literature consistently shows that performance outcomes depend on whether those outputs are legible to decision makers, compatible with business routines, and aligned with managerial priorities (Aditya & Chandra, 2022; Anick & Tasnim, 2022). This is particularly salient in digital economies where enterprises coordinate across functions, subsidiaries, platforms, and external partners (Ahmad & Van Looy, 2020; Hisham & Robel, 2022; Siddique & Amin, 2022). Under those conditions, AI-driven DSS serves as an infrastructural layer connecting analytics to resource allocation, customer management, workflow prioritization, service quality, compliance monitoring, and productivity management. The scholarly pattern is clear: intelligent decision support is strongest when analytical intelligence is institutionalized as an enterprise capability rather than treated as an isolated technical experiment (Borges et al., 2021; Md & Islam, 2022; Mehedi & Md, 2022).

The second major stream shaping this research title concerns business process automation and the transformation of process management under digital conditions. Business process management (BPM) scholarship has long examined how organizations design, execute, monitor, and improve work, while digital innovation research has shown that BPM is increasingly intertwined with AI, process mining, robotic process automation (RPA), and data-intensive enterprise platforms. A systematic review of BPM and digital innovations showed how technologies such as AI, IoT, blockchain, and process mining reconfigure process research and practice (Mainuddin & Chandra, 2022; Shahinur & Sultan, 2022). The literature on RPA has described it as a software-based mechanism for automating repetitive, rule-based tasks, while more recent work has detailed how RPA adoption is associated with execution-time reduction, process eligibility concerns, benefits, and implementation barriers (Moreira et al., 2023). Research on process mining has also characterized it as a form of business analytics for analyzing and improving processes, with distinct relevance for managerial decision making. Taken together, these studies show that intelligent business process automation is broader than routine task automation; it includes process discovery, conformance analysis, exception detection, workflow redesign, and the embedding of analytical or algorithmic logic into execution environments. This broader conception is highly relevant for AI-driven enterprise DSS because decision support no longer occurs only before or after process execution. In many enterprise contexts, decision logic is now integrated within the process itself, shaping approvals, routing, prioritization, escalation, forecasting, and control mechanisms in near-real time (Mostafa & Tohidul, 2022; Khatun & Morshedul, 2022). AI-driven decision support can classify cases, recommend actions, assign probabilities to outcomes, and optimize resource use, while process automation systems operationalize those outputs within enterprise workflows. The relationship is reciprocal: BPM provides the execution context and organizational structure; AI-driven DSS provides the analytical intelligence that informs or triggers process choices (Islam & Aditya, 2023; Phillips-Wren et al., 2021; Zakia & Khairum Nahar, 2022). In digital economies, where firms operate under high transaction volumes and distributed coordination requirements, this coupling of AI and automation becomes a defining feature of enterprise organization, linking data interpretation to the disciplined execution of business processes across functions and borders (Arnott & Pervan, 2005; Md Khaled & Mosheur, 2023; Shahab & Aditya, 2023).

Another important dimension in the literature is the organizational and theoretical framing of AI-driven decision support. Dynamic Capabilities Theory offers a strong explanation for why enterprise AI systems matter beyond technical efficiency: firms require the ability to sense changes in markets and operations, seize opportunities through timely action, and transform internal resources and routines to remain effective under volatility (Hasan Or et al., 2023; Mehedi & Nahar, 2023). AI-driven DSS fits this logic because it extends sensing through data collection and analysis, supports seizing through recommendation and prioritization, and facilitates transformation when analytical insight is incorporated into workflows, performance metrics, and decision rules. Yet dynamic capability alone does not exhaust the organizational reality of AI (Sultan & Anick, 2023; Mostafa, 2023). A sociotechnical framework for AI in organizations has shown that cognitive, relational, and structural conditions shape whether AI becomes productive within human systems, and a more recent systematic review identified organizational, information, and technology dimensions as central categories for AI implementation in organizations (Di Vaio et al., 2020; Ratul & Aditya, 2023; Tasnim & Zaheda, 2023). These contributions are valuable because enterprises do not adopt AI-driven DSS in a vacuum; they introduce such systems into settings defined by managerial authority, employee expertise, data governance, interdepartmental coordination, and process accountability. The sociotechnical angle helps explain why AI-driven decision support can alter work allocation, evaluation routines, communication channels, and procedural trust. The dynamic capability angle helps explain why such systems are linked to adaptability, responsiveness, and performance under change. Together, these perspectives frame enterprise AI decision support as both a strategic capability and an organizational arrangement. This is especially relevant to intelligent business process automation, where automation cannot be reduced to replacing manual effort. Automation reorganizes the relationship between human judgment, digital models, and process control (Iftekhar & Tohidul, 2024; Loureiro et al., 2021; Khaled & Morshedul, 2024). The literature accordingly points toward a form of enterprise intelligence in which managers, analysts, and automated systems interact through shared data infrastructures and embedded decision routines (Towhidul & Uddin, 2024; Mushfequr & Aditya, 2024). In such settings, AI-driven DSS functions as a connective mechanism between information processing and organizational action, while automation becomes the procedural expression of that intelligence across enterprise operations (Makarius et al., 2020; Sazzadul & Rebeka, 2024; Tasnim & Anick, 2024).

The international significance of studying AI-driven enterprise decision support systems is particularly visible in the digital transformation literature, which situates analytics, automation, and platform-enabled coordination within broad changes in business models, customer interaction, value creation, and interorganizational exchange (Md, 2025; Zaheda & Md Hamidur, 2024). Digital transformation has been conceptualized as a process through which digital technologies alter value-creation paths, organizational structures, and strategic responses, while multidisciplinary research has described stages of digitization, digitalization, and digital transformation and linked them to business-model change and new capability requirements. A large review of digital transformation research further showed that the field now spans core activities, peripheral activities, and external environments, indicating that the contemporary firm is increasingly embedded in digitally connected ecosystems (Karaboga et al., 2023; Md Khaled, 2025; Md Shahab, 2025). In parallel, AI-in-business reviews have shown that decision support and automation are two of the most prominent sources of business value associated with AI use in organizations. Related work has also connected AI to business-model development and value architecture, while automated machine learning has been discussed as part of AI-driven decision making in business analytics (Lee et al., 2023; Mostafa, 2025; Sazzadul, 2025). These studies together establish that AI-driven enterprise DSS is not a niche technical issue but part of a wider international reconfiguration of enterprise activity in data-rich markets. Firms operating in digital economies face expanded data environments, stronger demands for responsiveness, and more intensive coordination across customers, suppliers, regulators, and internal units. Under these conditions, the enterprise capacity to automate processes intelligently and support decisions analytically becomes a core organizational characteristic (Md Khaled, 2026; Akter & Aditya, 2025). The literature also shows that digital transformation is not uniform across organizations, which gives particular salience to enterprise readiness, management capability, data quality, and cultural alignment. Such variation is central for research that seeks to examine AI-driven decision support and intelligent business process automation in a quantitative and case-based manner, because it directs attention to measurable differences in how organizations structure analytical capability, integrate AI into processes, and realize performance outcomes within digital economies (Gupta & George, 2016).

Within this broad scholarly landscape, a clear research space remains around the integrated study of AI-driven enterprise decision support systems as a framework for intelligent business process automation. Existing literature is rich in reviews of AI in business, big data analytics capability, DSS foundations, BPM innovations, RPA, process mining, and digital transformation, yet these streams are frequently examined in parallel rather than in a single explanatory structure. DSS research identifies the decision-support lineage and clarifies the connection between data, models, and managerial judgment (Verhoef et al., 2021). Analytics capability research explains how resources and culture shape performance outcomes. BPM and automation research explains how work is executed, monitored, and redesigned through digital means (Verhoef et al., 2021; Vial, 2019). AI implementation research explains how organizational conditions shape adoption and use. What is less frequently specified in one model is how AI-driven decision support capability, enterprise-level automation logic, and measurable organizational outcomes such as process efficiency, decision quality, responsiveness, and productivity fit together in a single empirical account. That gap is especially important for digital economies, where process execution and decision quality are increasingly interdependent. An enterprise may possess advanced analytics, yet weak process integration can limit automation gains; another may automate workflows extensively, yet limited analytical depth can restrict decision quality and adaptability (Wamba et al., 2017). A research introduction for the present topic accordingly centers on this intersection: AI-driven DSS as the intelligence layer, business process automation as the execution layer, and digital economies as the competitive context in which both layers are organized, measured, and experienced (Zerbino et al., 2021). This framing provides the conceptual ground for examining enterprises not merely as technology adopters, but as organizational systems in which analytical capability and automated process design jointly structure managerial action and operational performance.

Background of the Study

The background of this study is rooted in the rapid transformation of modern enterprises from conventional, manually coordinated organizations into digitally connected systems that rely on data, analytics, and automation for everyday decision-making. In earlier business environments, many important organizational decisions were shaped by human judgment supported by periodic reports, static databases, and fragmented information systems. As markets became faster, more globalized, and more competitive, this traditional approach started to show clear limitations, especially in situations requiring real-time analysis, coordinated responses, and consistent process execution across departments and locations. At the same time, enterprises began to generate vast amounts of operational, transactional, customer, and process data through enterprise resource planning systems, customer relationship platforms, digital finance tools, supply chain applications, cloud services, and online business channels. This shift created the conditions for artificial intelligence to become a meaningful component of enterprise decision environments. Artificial intelligence-driven decision support systems emerged as a more advanced form of managerial support by combining data processing, predictive logic, pattern recognition, optimization, and automated recommendations within a single decision-oriented framework. In parallel, business process automation evolved from simple rule-based task execution into more intelligent forms of automation capable of adapting to data inputs, prioritizing actions, supporting workflow routing, and improving operational consistency. In digital economies, where firms are expected to respond quickly to customers, manage complex networks, maintain service quality, reduce operational delays, and make evidence-based decisions, the relationship between decision support and automation has become increasingly important. Enterprises are no longer concerned only with collecting information; they are also concerned with converting information into timely action, embedding intelligence into business processes, and ensuring that automated workflows are aligned with strategic and operational objectives. This background makes the study highly relevant because it addresses an important organizational reality: firms increasingly depend on intelligent systems not only to inform managerial choices but also to shape how business processes are executed, monitored, and optimized. As a result, understanding how artificial intelligence-driven enterprise decision support systems contribute to intelligent business process automation is essential for explaining how modern organizations function within data-intensive and digitally integrated economic environments.

Problem Statement

The problem addressed in this study arises from the growing mismatch between the increasing complexity of enterprise decision environments and the limited ability of many organizations to integrate intelligent decision support with business process automation in a coordinated and effective manner. In many enterprises, decision-making and process execution still operate as partially separate functions, where managers rely on reports, dashboards, or fragmented analytical tools while operational processes continue through conventional automated or semi-manual workflows. This separation reduces the speed, accuracy, and consistency with which data-driven insights are transformed into organizational action. As enterprises operate in digital economies marked by high data volumes, rapid market shifts, customer expectations for immediacy, and interconnected business systems, the need for intelligent, adaptive, and process-oriented decision support has become more critical. Many organizations have adopted some form of artificial intelligence, business analytics, or process automation, yet these technologies are often implemented in isolated ways that do not fully support enterprise-wide coordination, continuous decision quality, or workflow responsiveness. In such conditions, AI tools may generate recommendations without being embedded in actual business processes, while automated systems may execute tasks efficiently without benefiting from higher-level decision intelligence. This creates an operational gap in which enterprises possess digital tools but do not fully realize their combined value. Another important dimension of the problem is that the organizational outcomes of AI-driven decision support are not always clearly measured in relation to process efficiency, decision quality, responsiveness, and productivity. There is also limited empirical clarity regarding the readiness conditions that enable enterprises to successfully connect decision intelligence with intelligent automation. Without a structured understanding of how AI-driven enterprise decision support systems influence business process automation, organizations may struggle to justify investments, design effective integration strategies, or identify the factors that strengthen or weaken performance outcomes. The central problem, therefore, is not only the adoption of artificial intelligence in enterprises, but the insufficient understanding of how AI-driven decision support can serve as a coherent framework for intelligent business process automation in digitally integrated economic environments.

Objectives of the Study

The objective of this study is to examine how artificial intelligence-driven enterprise decision support systems contribute to intelligent business process automation within digital economies by focusing on the organizational mechanisms through which data-driven intelligence is converted into operational action. More specifically, the study seeks to investigate the extent to which AI-driven decision support capability improves business process efficiency by enabling enterprises to make faster, more accurate, and more coordinated decisions across their functional activities. It also aims to analyze how AI-enabled analytics enhances decision quality through improved information processing, pattern recognition, and analytical support for managerial judgment. Another objective is to assess the influence of automation intelligence on organizational responsiveness, particularly in environments where enterprises must react quickly to operational demands, customer expectations, and changing market conditions. In addition, the study intends to determine whether the integration of AI-driven decision support systems leads to measurable gains in productivity and operational effectiveness by strengthening workflow alignment, reducing delays, and supporting smarter resource utilization. A further objective is to evaluate the role of enterprise decision-automation readiness, including factors such as data quality, system integration, employee capability, and managerial support, in shaping the relationship between AI-driven DSS and intelligent business process automation outcomes. Through these objectives, the study aims to move beyond a general discussion of AI adoption and instead provide a focused examination of how enterprise intelligence and automation interact within real organizational settings. The study also seeks to develop a structured framework that explains the relationship among AI capability, decision support, readiness conditions, and automation performance. In this way, the objective of the research is both analytical and organizational: analytically, it aims to measure relationships among key study variables using quantitative methods, and organizationally, it aims to clarify how enterprises can understand the functional role of AI-driven decision support systems in the broader automation of business processes within data-intensive and digitally connected economies.

Research Hypotheses

The research hypotheses of this study are developed from the central assumption that artificial intelligence-driven enterprise decision support systems have a measurable and positive relationship with intelligent business process automation and its major performance dimensions. The hypotheses are intended to translate the conceptual logic of the study into testable statements that can be examined through descriptive statistics, correlation analysis, and regression modeling. In this context, the first hypothesis proposes that AI-driven decision support capability has a significant positive effect on business process efficiency, based on the expectation that stronger analytical and decision-support functions enable smoother workflow coordination, reduced delays, and improved process accuracy. The second hypothesis states that AI-enabled analytics has a significant positive effect on decision quality, reflecting the view that better use of enterprise data, predictive logic, and analytical recommendations improves the consistency and soundness of managerial and operational judgments. The third hypothesis proposes that automation intelligence has a significant positive effect on organizational responsiveness, on the grounds that enterprises with more intelligent and adaptive automation systems are better able to respond to changing internal and external demands. The fourth hypothesis states that AI-driven DSS adoption has a significant positive effect on productivity and operational effectiveness, suggesting that the integration of AI-supported decision mechanisms into enterprise systems improves output, coordination, and resource efficiency. The fifth hypothesis proposes that enterprise decision-automation readiness significantly influences the strength of the relationship between AI-driven decision support capability and intelligent business process automation, indicating that the benefits of AI-driven DSS are shaped by the organizational environment in which such systems are deployed. These hypotheses provide a structured path for examining not only whether AI-driven decision support systems matter, but also how they matter across different dimensions of enterprise performance. They help convert a broad research topic into measurable relationships among clearly defined variables and support a more systematic investigation of the role of intelligent decision support in modern business automation.

Significance of the Research

This research is significant because it addresses an important and timely organizational issue within digital economies, namely the growing need to understand how artificial intelligence-driven decision support systems can strengthen intelligent business process automation in enterprise settings. The value of the study can be understood across several dimensions:

i. Academic significance: The study contributes to the body of knowledge on artificial intelligence, enterprise decision support systems, and business process automation by bringing these related areas together within one structured research framework. It helps clarify how decision intelligence and process automation interact as part of the same organizational system rather than as separate technological developments.

ii. Theoretical significance: The research strengthens theoretical understanding by linking enterprise AI capability, automation readiness, and organizational outcomes in a measurable way. It offers a basis for explaining how intelligent decision support functions within broader enterprise capability structures and how those structures shape operational performance.

iii. Methodological significance: The study is significant in methodological terms because it applies a quantitative, cross-sectional, case-study-based design to a topic that is often discussed in broad conceptual terms. By using Likert-scale measurement, descriptive statistics, correlation, and regression analysis, the research provides a structured empirical approach to assessing relationships among the main variables.

iv. Managerial significance: The study is useful for managers and organizational leaders because it provides clearer insight into how AI-driven DSS can support process efficiency, decision quality, responsiveness, and productivity. This can help enterprise leaders make more informed choices about digital investments, workflow design, and decision infrastructure.

v. Operational significance: The research is important for enterprise operations because it highlights the role of intelligent systems in improving how workflows are executed, monitored, and aligned with business objectives. It draws attention to the practical conditions that support stronger automation outcomes.

vi. Strategic significance: The study has strategic value because enterprises in digital economies require systems that support adaptability, speed, and coordinated action. Understanding the contribution of AI-driven DSS to process automation supports broader digital transformation and competitive positioning.

vii. Policy and institutional significance: The research may also support institutions, planners, and organizational policymakers by showing the importance of readiness factors such as data quality, system integration, employee skills, and managerial support in building responsible and effective enterprise AI environments.

LITERATURE REVIEW

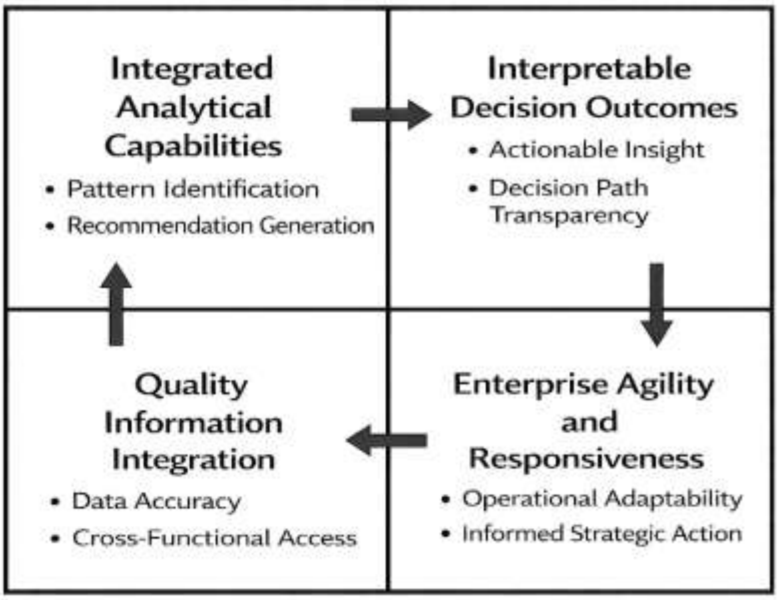
The literature review for this study is designed to establish the conceptual, theoretical, and empirical foundation for understanding artificial intelligence-driven enterprise decision support systems as a framework for intelligent business process automation in digital economies. The review begins from the recognition that the study stands at the intersection of several closely related knowledge areas, including artificial intelligence, decision support systems, business analytics, enterprise systems, business process automation, and digital transformation. Each of these areas contributes an important part of the overall explanation of how modern organizations use data, models, and digital technologies to improve decisions and coordinate operational activities. The literature is therefore not examined as a collection of unrelated themes, but as a structured body of knowledge that helps explain how analytical intelligence becomes embedded in organizational processes and how this integration influences enterprise performance. In this study, the literature review serves several purposes. First, it clarifies the meaning and scope of the core concepts used throughout the research, especially AI-driven decision support systems, automation intelligence, business process efficiency, decision quality, responsiveness, and productivity. Second, it identifies the main theoretical lens through which the study is interpreted, allowing the research to move beyond description and toward a more systematic explanation of organizational capability and performance. Third, it maps the conceptual framework of the study by identifying the relationships among the independent, dependent, and moderating variables. Fourth, it examines prior empirical studies in order to show what has already been established, where inconsistencies remain, and which important issues have not yet been sufficiently explored. This is especially relevant because current research often addresses artificial intelligence, analytics, and automation in separate discussions, while enterprise practice increasingly combines them in integrated digital environments. The literature review therefore creates the scholarly basis for the present study by synthesizing existing knowledge into a focused argument that supports the research problem, objectives, and hypotheses. It also provides the foundation for the methodological choices of the study by identifying measurable constructs and relevant lines of evidence from earlier research. In this sense, the literature review is not only a summary of previous work, but a structured analytical section that connects past scholarship to the present investigation of intelligent enterprise decision support and automation.

Artificial Intelligence in Enterprise Decision Support Systems

Artificial intelligence in enterprise decision support systems can be understood as the integration of machine-based analytical capabilities into organizational platforms that assist managers and professionals in interpreting data, evaluating alternatives, and selecting appropriate courses of action. In enterprise environments, decision support is no longer confined to static reporting or isolated executive dashboards. It increasingly involves systems that combine large volumes of structured and unstructured data with analytical models capable of identifying patterns, generating recommendations, and supporting both routine and non-routine decisions. This evolution is significant because modern organizations operate through interconnected information flows across finance, operations, supply chains, customer management, and strategic planning. The enterprise value of intelligent decision support lies in its ability to connect those information flows to actual decision processes in a timely and usable form (Isik et al., 2013). A process-oriented view is particularly important in explaining this value, because the worth of enterprise intelligence is not measured only by the existence of data repositories or analytical software, but by the degree to which such systems improve business processes and organizational outcomes. Research on business intelligence systems showed early on that decision-oriented analytical systems are most meaningful when they influence business process performance and translate that improvement into broader organizational performance. That work established a strong foundation for the later move toward AI-enhanced decision support by demonstrating that enterprise analytics has operational consequences, not only informational ones. As analytical systems became more sophisticated, the emphasis moved from simple reporting toward integrated intelligence that could actively support decision making across organizational levels. In that sense, enterprise decision support systems became more than technical repositories of information; they became capability platforms through which firms organize evidence, evaluate alternatives, and strengthen managerial action under conditions of complexity and speed. The contemporary AI-driven decision support system therefore represents an extension of the enterprise intelligence tradition, grounded in the idea that better data, stronger analytical architecture, and closer alignment with business processes produce more effective decisions within the organization (Elbashir et al., 2008).

The literature also shows that the success of enterprise decision support does not depend only on the technical presence of analytical tools, but on the quality of the capabilities that surround their use. Decision support systems in enterprise settings must provide reliable access to data, integration across information sources, and analytical functions that suit the context of managerial action. This capability perspective is central because intelligent systems are only valuable when their outputs can be interpreted, trusted, and applied within real organizational decisions. Studies on business intelligence success have highlighted that technological capabilities such as data quality, user access, and integration with other enterprise systems are fundamental to achieving meaningful decision-support outcomes (Ashrafi et al., 2019). At the same time, the decision environment influences how these capabilities are leveraged, which means that enterprise decision support should always be examined in relation to the nature of the decisions being made and the context in which managers operate. Related work on the quality of managerial decision making has further shown that the effect of business intelligence is not merely direct; it is mediated by factors such as information quality and the scope of the analytical solution. This point is highly relevant to artificial intelligence in enterprise systems because AI-driven decision support does not automatically improve managerial judgment by virtue of computational sophistication alone. Its influence depends on whether the system produces information that is sufficiently relevant, timely, and comprehensible to decision makers. Enterprise AI therefore needs to be understood as a layered support structure in which algorithmic capabilities, information quality, and managerial use operate together. In practical terms, this means that AI in enterprise decision support is not simply a technical upgrade to existing systems. It is a reconfiguration of how organizations access knowledge, interpret signals, and coordinate action through an intelligence architecture that supports both efficiency and judgment. The emphasis on capability quality and decision-making quality makes this literature especially relevant for understanding why some enterprise decision support systems produce high organizational value while others remain underutilized or strategically weak (Benbya et al., 2021).

Figure 2: AI-Based Enterprise Decision Support: Linking Data Integration, Insight, And Organizational Responsiveness



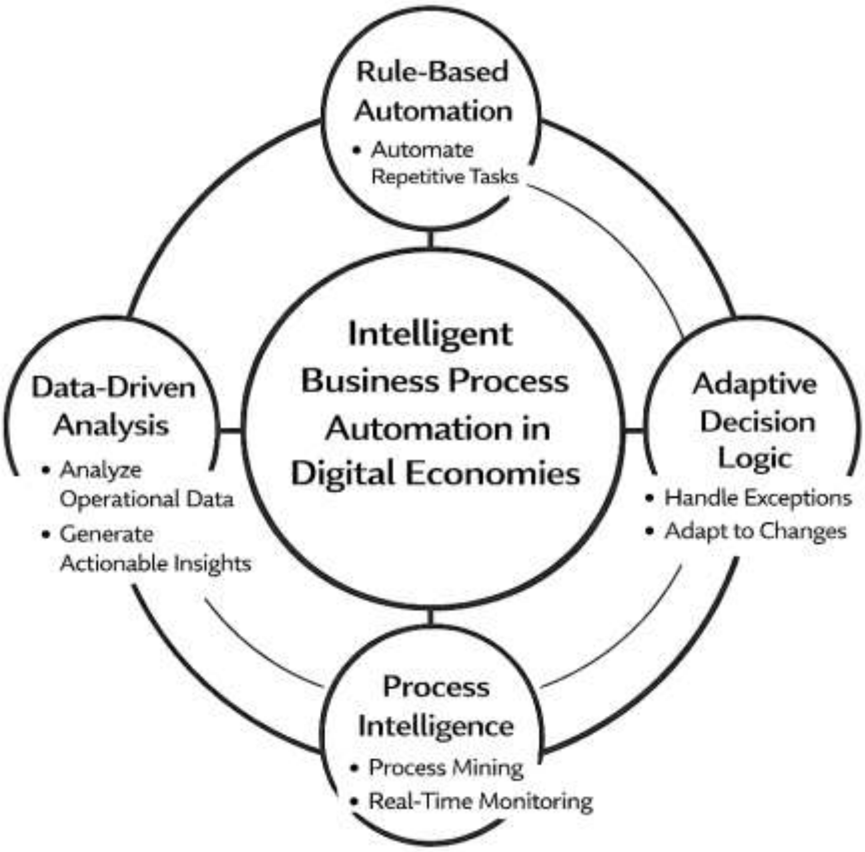
A more recent strand of scholarship extends this understanding by linking enterprise decision support to broader organizational agility and by explicitly identifying artificial intelligence as a distinctive organizational capability. This literature suggests that intelligent decision support should not be viewed only as a reporting or forecasting function, but as part of a wider system through which organizations sense change, process information rapidly, and respond through coordinated action. Research on business analytics capabilities has shown that the analytical strength of the firm contributes to agility and performance by improving information quality and enhancing innovation capability. This perspective broadens the logic of decision support by showing that enterprise intelligence affects not only immediate managerial choices but also the organization's capacity to react and adapt. Within AI-oriented scholarship, the argument becomes even more explicit: artificial intelligence technologies generate important organizational capabilities in areas such as automation, engagement, innovation, and insight-driven decision making (Elbashir et al., 2008). This view places enterprise decision support within a larger transformation of organizational systems, where intelligence is embedded not just in dashboards or analytical reports but in the ongoing mechanisms of enterprise coordination. AI-driven decision support systems therefore occupy a central place in the architecture of digital organizations because they connect data processing, model-based reasoning, and managerial interpretation with execution-oriented enterprise processes. The conceptual shift here is important for the present study. Earlier enterprise decision support focused on helping managers make better decisions; current AI-enabled systems increasingly shape how organizations detect issues, prioritize responses, and align decisions with automated or semi-automated workflows. As a result, artificial intelligence in enterprise decision support systems should be interpreted as an organizationally embedded capability that strengthens analytical responsiveness, supports strategic and operational adaptation, and deepens the integration between insight generation and enterprise action. This framing is especially useful for a study concerned with intelligent business process automation, because it clarifies that decision support is not separate from enterprise transformation but one of its core enabling mechanisms (Wieder & Ossimitz, 2015).

Intelligent Business Process Automation in Digital Economies

Intelligent business process automation in digital economies refers to the use of digital technologies to execute, coordinate, monitor, and improve organizational processes through a combination of rule-based automation, data-driven analysis, and adaptive decision logic. Within enterprise settings, this concept extends beyond traditional workflow automation because it joins process execution with analytical intelligence, allowing organizations to manage repetitive tasks, exceptions, approvals, and information flows with greater speed and consistency. Digital economies intensify the relevance of this form of automation because firms increasingly operate through connected platforms, cloud services, cross-functional systems, and high-volume digital transactions that demand continuous process reliability. In this context, process automation is not only a technical convenience; it becomes a structural mechanism through which firms sustain service delivery, operational discipline, and timely response across distributed business environments. The literature on robotic process automation identifies this shift clearly by describing RPA as a contemporary answer to the long-standing question of what organizational work should be executed by humans and what can be delegated to software agents, particularly when processes are repetitive, standardized, and digitally traceable (Van Looy, 2021). Related work has also shown that the relationship between business process management and digital innovation is positive but shaped by context, indicating that process-oriented organizations use digital innovation not merely to automate existing routines but to transform how processes are designed, aligned, and improved (van der Aalst et al., 2018). This framing is highly relevant to digital economies because enterprises do not gain advantage from automation in isolation; they gain advantage when automation contributes to broader process performance, strategic flexibility, and organizational responsiveness. Intelligent business process automation therefore represents a more advanced stage of enterprise process management in which organizations seek not only execution efficiency but also process intelligence, process visibility, and the capability to connect workflow action with evolving digital business demands. In such environments, automation becomes a critical part of how enterprises structure operational consistency and coordinate process outcomes across departments, markets, and digital channels.

A second important feature of intelligent business process automation is its close connection to digital innovation and the changing assumptions of business process management. Traditional process management was often concerned with documenting, standardizing, and incrementally improving organizational routines. In digital economies, process environments are more fluid because organizations must integrate emerging technologies, react to shifting customer expectations, and redesign workflows in response to real-time information. Research connecting business process management with digital innovation argues that these two streams should not be treated as separate conversations, because process management provides discipline and structure while digital innovation introduces new possibilities for redesign, experimentation, and service transformation (Thiede et al., 2018). This insight matters for intelligent automation because enterprises must align exploration and control rather than choosing one over the other. Process automation that only reproduces existing routines may increase speed without strengthening adaptability, whereas digital innovation without process structure may create fragmented change without sustainable operational value. Studies of process mining reinforce this view by showing that organizations use process mining to generate detailed knowledge about how processes actually unfold, which helps uncover bottlenecks, variation, and cross-system coordination problems that are not always visible through formal process documentation alone (vom Brocke et al., 2020). That capability is central to intelligent automation because automation decisions depend on understanding real execution patterns, data availability, and process interdependencies. In digital economies, where process steps are recorded across enterprise systems, process mining supports a more evidence-based approach to automation by revealing where standardization, exception handling, and redesign are most needed. As a result, intelligent business process automation is best understood as a process-aware and data-informed organizational capability. It combines automation technologies with process knowledge so that digital work is not only faster but also better aligned with enterprise goals, customer requirements, and the realities of operational complexity. This perspective places process intelligence at the center of automation and shows why business process management remains essential in digitally evolving enterprises.

Figure 3: Intelligent Business Process Automation In Digital Economies: A Process-Aware Capability Framework



A third dimension of this literature concerns the organizational conditions and broader outcomes associated with intelligent automation. Intelligent business process automation is often presented as a route to efficiency, yet recent scholarship shows that its implementation is shaped by technological readiness, organizational context, human concerns, and managerial strategy. Research on intelligent automation implementation in multinational firms found that internal conditions such as absorptive capacity, social capital competency, and employee socio-behavioral concerns strongly influence how firms adopt and use intelligent automation, while the resulting performance effects extend beyond narrow efficiency gains to economic, environmental, and social dimensions (Ghobakhloo et al., 2023). This finding is highly relevant for digital economies because enterprise automation rarely occurs in a purely technical domain. It unfolds within organizations where data governance, employee acceptance, process ownership, and managerial legitimacy affect whether automated systems are trusted, sustained, and scaled. When considered together with the literature on RPA and process-oriented digital innovation, a broader picture emerges: intelligent business process automation is a socio-technical enterprise capability rather than a simple software deployment. It depends on the fit between process structure, digital trace data, organizational readiness, and the strategic intent behind automation initiatives. In digital economies, this fit is particularly important because firms face simultaneous pressures for cost control, service quality, process transparency, and responsiveness. Intelligent automation addresses these pressures by embedding digital logic into business processes, yet its organizational value depends on the extent to which automation is supported by process understanding and aligned with enterprise priorities. For this reason, the literature positions intelligent business process automation as a core component of digitally transformed enterprises: it links operational workflows to analytical and technological capabilities, supports more coordinated process execution, and helps organizations manage complexity in environments characterized by speed, connectivity, and ongoing digital change. This makes intelligent automation a central concept for examining how enterprises convert digital capability into disciplined and scalable process performance.

Operational Outcomes of AI-Driven Enterprise Decision Support Systems

A major concern in the literature on AI-driven enterprise decision support systems is the nature of their operational outcomes within firms that rely on digital information, analytical capability, and coordinated process execution. Operational outcomes refer to the measurable improvements that arise when intelligent decision support becomes embedded in enterprise activities, especially in terms of efficiency, process performance, decision quality, and broader organizational effectiveness. In enterprise settings, these outcomes are not created simply by installing sophisticated analytical tools; they emerge when data acquisition, analytical processing, and decision-oriented outputs are connected to the real flow of business operations. One important contribution to this line of reasoning is the argument that business analytics adoption influences firm performance through business process performance. This means that enterprise-level benefits are not only direct financial or strategic gains but are first expressed through better execution of processes, clearer workflows, and stronger coordination between information use and operational action. This process-centered understanding is highly relevant to AI-driven decision support because AI systems often generate recommendations, classifications, and forecasts that become valuable only when they influence how tasks are carried out inside the firm. The literature therefore positions operational performance as the point where analytical intelligence is translated into enterprise value (Aydiner et al., 2019). A related strand of work argues that big data analytics capability also improves firm performance when it is aligned with business strategy. In this view, operational outcomes depend not only on the presence of technical and managerial analytics capability but also on whether that capability supports the organization's strategic priorities and process needs. This is particularly significant for AI-driven decision support systems because enterprises may possess advanced analytics and still experience limited operational benefit if those systems are disconnected from workflow realities, managerial expectations, or the performance logic of the firm. Together, these studies show that operational gains from enterprise intelligence emerge through process alignment, strategic fit, and the ability of the organization to use analytical insight in ways that directly shape business execution and measurable performance outcomes (Akter et al., 2016).

A second major operational outcome discussed in the literature concerns decision quality, which is especially important for AI-driven enterprise decision support systems because their central organizational promise lies in improving the quality of managerial and operational judgments. Decision quality refers to the extent to which organizational choices are timely, informed, accurate, and useful for achieving intended outcomes. Research in this area shows that the use of data analytics does not automatically improve decision quality; rather, its effect is shaped by intermediate factors such as knowledge sharing, data analytics competency, data quality, and data diagnosticity (Ghasemaghaei, 2019b). One study demonstrated that the use of data analytics improves firm decision-making quality through knowledge sharing and through the firm's ability to effectively deploy analytics-related resources. This finding is important because it shows that AI-driven decision support should not be treated as a solitary technical intervention. Its impact on enterprise operations depends on whether knowledge derived from data is effectively circulated within the organization and whether managers possess the capability to interpret and apply analytical outputs. Another study showed that big data can improve firm decision quality when data quality and data diagnosticity are sufficiently strong. This reinforces the view that enterprise decision support systems operate within a chain of conditions: data must be credible, insights must be meaningful, and analytical outputs must be usable in actual decision contexts. For AI-driven systems, this means that operational success depends on much more than algorithmic sophistication. It depends on the enterprise's ability to transform raw and varied data into diagnostically useful intelligence and then integrate that intelligence into real decisions involving planning, prioritization, control, and coordination. In practical terms, this research highlights a core operational principle: decision support systems improve enterprise functioning not merely by generating more information, but by producing better-quality decisions that shape how resources are allocated, how exceptions are handled, and how business activities are directed across functions. Operational outcomes are therefore strongly linked to the internal knowledge processes and data conditions that make AI-generated intelligence actionable inside the enterprise (Ghasemaghaei, 2019a).

Figure 4: Ai-Driven Decision Support And Its Impact On Enterprise Performance And Responsiveness

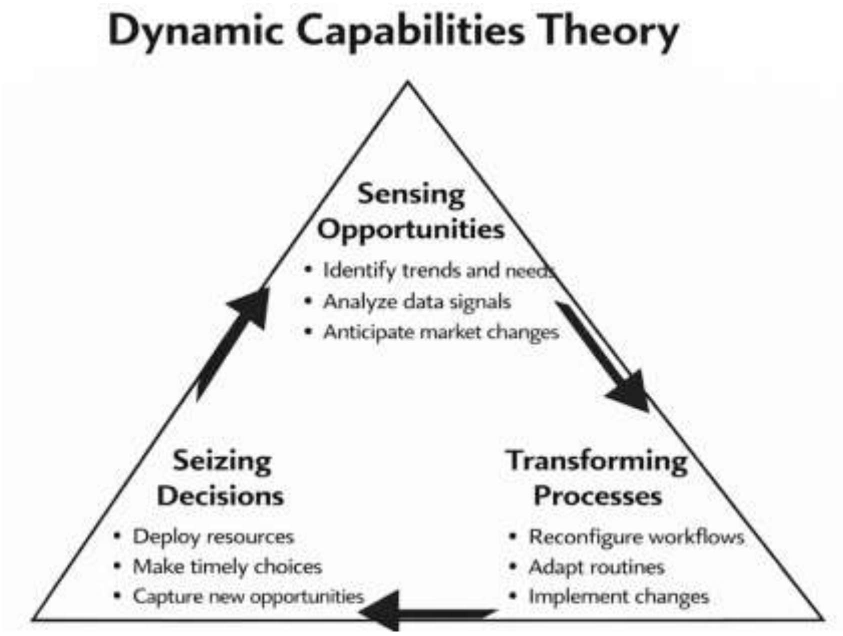
A third operational outcome emphasized in the literature is the strengthening of organizational capabilities that support responsiveness, competitiveness, and adaptive execution. AI-driven enterprise decision support systems increasingly influence firm operations by helping organizations respond more quickly to changing information conditions, customer needs, and internal process demands. The literature on big data analytics capability and competitive performance shows that the value of analytics is mediated by dynamic and operational capabilities. This means that AI-driven decision support contributes to performance when it helps firms build the ability to reconfigure resources, strengthen operational routines, and turn analytical insight into competitive action. Such a view expands the meaning of operational outcomes beyond narrow efficiency measures and includes agility, responsiveness, and coordinated adaptation as central dimensions of enterprise performance. For digital enterprises, these outcomes are highly significant because operational environments are rarely static (Mikalef et al., 2020). Managers must respond to demand variation, service issues, supply uncertainties, compliance expectations, and shifting market conditions while maintaining process continuity. AI-driven decision support systems contribute to this context by enabling faster interpretation of data, more informed prioritization of tasks, and more coordinated execution across functions. The operational significance of these systems is therefore visible in how they support both routine control and adaptive action. Rather than functioning only as analytical back-office tools, they become organizational mechanisms that connect insight generation with action under changing conditions. This is why operational outcomes in the present study should be understood in a multidimensional way that includes process performance, decision quality, responsiveness, and broader enterprise effectiveness. The literature suggests that these outcomes are interconnected: stronger analytics capability improves the quality of insight, better-quality insight improves decision quality, improved decision quality enhances process execution, and stronger process execution contributes to firm-level performance and competitiveness. In this sense, AI-driven enterprise decision support systems are operationally meaningful because they help firms organize intelligence in a form that supports both disciplined process execution and agile enterprise action in complex digital economies (Ghasemaghaei, 2019a).

Dynamic Capabilities Theory

Dynamic Capabilities Theory provides the most suitable theoretical lens for this study because it explains how firms renew, reconfigure, and redeploy resources when operating in volatile, technology-intensive environments. In the dynamic capabilities literature, the firm is not viewed only as a holder of valuable resources, but as an actor that must continuously adjust its resource base, organizational routines, and strategic posture in order to remain effective under changing conditions. This logic is especially relevant to research on artificial intelligence-driven enterprise decision support systems because AI does not create enterprise value simply through technological possession; value emerges when the organization can mobilize, combine, and redirect data, analytics, managerial attention, and process infrastructures toward timely decisions and coordinated action. Barreto's review is especially helpful here because it synthesized fragmented streams of dynamic capabilities research and argued that dynamic capability is best understood as a multidimensional construct involving the propensity to sense opportunities and problems, make timely decisions, and change the firm's resource base accordingly (Barreto, 2010). That definition aligns closely with the present research topic, where enterprises are expected to sense operational signals through data, seize opportunities through AI-supported decisions, and transform internal processes through automation and workflow redesign. Dynamic Capabilities Theory therefore offers more than a general strategic vocabulary; it gives this study an explanatory structure for connecting enterprise intelligence to process change. AI-driven decision support systems can be interpreted as part of a sensing-and-seizing architecture because they help organizations capture data, generate recommendations, classify alternatives, and support managerial judgment. Intelligent business process automation fits the transforming dimension because it embeds those analytical outputs into routines, approvals, controls, and execution pathways. In digital economies, where firms face rapid data flows, interconnected platforms, and continuous operational adjustment, the ability to build and deploy such capabilities becomes central to enterprise functioning. For this reason, Dynamic Capabilities Theory is theoretically appropriate for explaining why some firms convert AI and decision support into meaningful automation outcomes while others struggle to connect intelligence, responsiveness, and process execution in a coherent enterprise system (Warner & Wäger, 2019).

A second reason this theory is highly applicable to the present study is that it clarifies the difference between merely operating efficiently and adapting effectively under changing conditions. Drnevich and Kriauciunas showed that ordinary capabilities and dynamic capabilities both contribute to relative firm performance, but that dynamic capabilities become especially important under greater environmental dynamism and heterogeneity (Drnevich & Kriauciunas, 2011). This distinction is essential for a study of AI-driven enterprise decision support and intelligent business process automation. Many enterprises can automate routine tasks or maintain stable information systems, which would correspond more closely to ordinary capabilities. The strategic issue in digital economies, however, is whether firms can adjust decisions, redesign workflows, and reconfigure process logic when customer demands, data conditions, competitive pressures, or operational contexts change quickly. That is where dynamic capabilities become analytically stronger than static capability explanations. Within this study, AI-driven enterprise decision support systems represent more than informational efficiency tools; they are mechanisms that can strengthen the organization's ability to detect changing conditions, evaluate responses, and coordinate action through automated and semi-automated processes. The literature on managerial cognitive microfoundations reinforces this point by showing that dynamic capabilities are not abstract organizational properties detached from leadership and judgment. Helfat and Peteraf argued that managerial cognitive capabilities underpin sensing, seizing, and reconfiguring because managers must interpret signals, focus attention, solve problems, and guide strategic change (Helfat & Peteraf, 2015). This insight is particularly relevant for enterprise AI because decision support systems still operate within managerial and organizational contexts. AI-generated outputs must be interpreted, trusted, and translated into process choices, escalation rules, or operational priorities. Dynamic Capabilities Theory is therefore valuable for this research because it bridges managerial judgment and organizational adaptation. It explains why AI-enabled decision support should not be treated as a purely technical artifact and why intelligent automation should not be reduced to routine digital execution. Instead, both are understood as parts of a broader adaptive capability through which enterprises sense changes, seize opportunities through informed decisions, and reconfigure business processes to sustain effective performance in digital economies (Drnevich & Kriauciunas, 2011).

Figure 5: Dynamic Capabilities Perspective On Ai-Driven Decision Support And Automation



The theory becomes even more compelling when applied to digital transformation and enterprise technology capability. Warner and Wäger's process model showed that incumbent firms build dynamic capabilities for digital transformation through digitally based sensing, seizing, and transforming microfoundations, and they emphasized agility as a core mechanism of ongoing strategic renewal. This is directly relevant to the present research because digital economies require organizations not only to digitize operations but also to renew business processes continuously through better information, quicker decisions, and more adaptive execution systems. In the same spirit, Mikalef and Pateli found that IT-enabled dynamic capabilities contribute to competitive performance indirectly through organizational agility, which suggests that technology-enabled reconfiguration matters because it enhances the enterprise's ability to respond and adjust rather than because it exists as infrastructure alone (Mikalef & Pateli, 2017). These findings provide a strong theoretical bridge to AI-driven decision support systems. If AI capability strengthens the firm's capacity to process data and generate actionable intelligence, and if intelligent automation embeds such intelligence into workflows, then the joint outcome should be observable in higher process efficiency, better decision quality, stronger responsiveness, and improved operational effectiveness. For this reason, Dynamic Capabilities Theory supports the full conceptual structure of the study by linking enterprise resources, managerial interpretation, process redesign, and performance outcomes within a single framework. The most suitable formula for the whole study, derived from this theoretical logic and intended for the regression stage, is:

$$IBPA = \beta_0 + \beta_1 AIDSC + \beta_2 AEA + \beta_3 AUTINT + \beta_4 EAR + \beta_5 (AIDSC \times EAR) + \varepsilon$$

Where **IBPA** represents intelligent business process automation, **AIDSC** represents AI-driven decision support capability, **AEA** represents AI-enabled analytics, **AUTINT** represents automation intelligence, **EAR** represents enterprise automation readiness, and **AIDSC × EAR** captures the moderating effect of readiness on the relationship between AI-driven decision support capability and automation outcomes.

Conceptual Framework

The conceptual framework of this study is developed to explain how artificial intelligence-driven enterprise decision support systems function as an enabling structure for intelligent business process automation in digital economies. At the center of the framework is the assumption that enterprises do not gain meaningful automation outcomes from digital technologies simply by acquiring tools; they gain those outcomes when analytical capabilities, decision processes, and operational systems are aligned in a coherent organizational logic. For this reason, the framework identifies AI-driven decision support capability, AI-enabled analytics, and automation intelligence as the main explanatory variables, while intelligent business process automation serves as the core dependent construct expressed through process efficiency, decision quality, organizational responsiveness, and productivity-related outcomes. The framework also incorporates enterprise automation readiness as a contextual and moderating variable because the literature shows that digital value depends on whether firms possess the organizational conditions needed to translate technological potential into embedded operational use. Research on organizational AI readiness is particularly important here because it demonstrates that successful AI deployment depends on assets, capabilities, and commitment rather than on technological availability alone. This means that enterprises must be sufficiently prepared in terms of data quality, managerial support, employee understanding, and structural fit before AI-driven decision support can be integrated effectively into business processes. In the same direction, studies on AI capability show that organizational performance effects arise indirectly through process automation and insight generation, which supports the present framework's assumption that enterprise decision support influences outcomes by reshaping operational mechanisms rather than acting as a stand-alone technological input. The conceptual model therefore treats AI-driven decision support systems as capability platforms that connect enterprise data resources to process-level action. In this structure, readiness explains whether the organization is capable of adopting and embedding intelligent decision support, while the main predictor variables explain how analytical intelligence is converted into actual process automation outcomes. The framework is therefore not only technological but organizational, since it recognizes that enterprise performance emerges from the interaction between analytical capability, process design, and implementation conditions within the firm (Jöhnk et al., 2021).

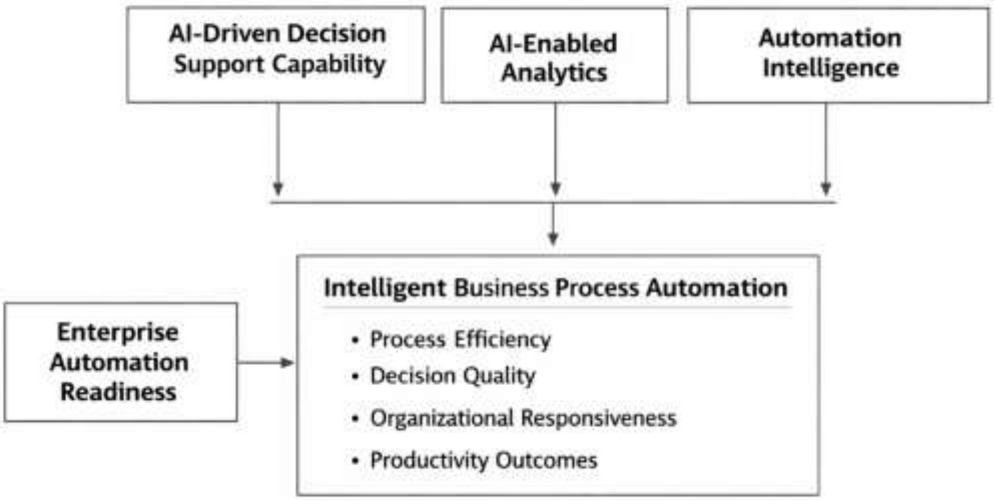
A second layer of the conceptual framework concerns the relationships among the independent variables and the expected organizational pathway through which they affect automation outcomes. AI-driven decision support capability refers to the enterprise's ability to use AI-supported systems for generating recommendations, identifying patterns, supporting judgments, and improving the timeliness and structure of managerial decisions. AI-enabled analytics refers to the organization's ability to process and interpret data in ways that strengthen insight, analysis, and evidence-based action. Automation intelligence refers to the degree to which business processes are digitally executed with adaptive, data-informed, and decision-oriented logic rather than only static rule execution. These constructs are conceptually distinct, yet the framework assumes that they reinforce one another. AI-driven decision support capability provides the intelligence base for decisions, AI-enabled analytics strengthens the quality and depth of evidence used in those decisions, and automation intelligence embeds the resulting logic into enterprise workflows. This relational understanding is supported by research showing that big data analytics capability becomes more valuable when aligned with business strategy and when translated into organizational agility and performance. It is also supported by research demonstrating that digital-related capabilities do not produce performance gains in isolation;

rather, they work through mediating organizational systems such as performance measurement and coordination mechanisms. In addition, work on business model innovation suggests that analytics capabilities influence broader organizational transformation when they activate strategic orientation and value-creation processes. These findings are important for the present study because they justify a framework in which enterprise intelligence is connected to enterprise execution through several linked mechanisms rather than through a single direct path. In conceptual terms, the study therefore assumes a chain of influence: AI capability strengthens analytical support, analytical support improves the quality and speed of enterprise decisions, and better-quality decisions improve the intelligence and effectiveness of business process automation. This logic can be expressed in a general functional form as:

$$IBPA = f(AIDSC, AEA, AUTINT, EAR)$$

where IBPA = intelligent business process automation, AIDSC = AI-driven decision support capability, AEA = AI-enabled analytics, AUTINT = automation intelligence, and EAR = enterprise automation readiness. This formula summarizes the central proposition that automation outcomes are a function of enterprise intelligence capability and the contextual readiness that supports its implementation (Ciampi et al., 2021; Nasiri et al., 2020).

Figure 6: Ai-Driven Decision Support And Automation: A Moderated Conceptual Framework



The full conceptual framework for the study is therefore best represented as a moderated explanatory model in which the three main predictor variables influence intelligent business process automation directly, while enterprise automation readiness conditions the strength of the relationship between AI-driven decision support capability and the dependent variable. This is appropriate because readiness is not merely another background factor; it shapes whether analytical outputs can be embedded into processes, accepted by users, and sustained across departments. In practical terms, an enterprise may possess sophisticated AI-enabled analytics, yet weak integration, low user preparedness, or limited managerial support can reduce the effect of those capabilities on process automation. By contrast, enterprises with stronger readiness are more likely to convert analytical capacity into efficient workflow design, faster response, and more reliable execution. The conceptual framework therefore aligns closely with the logic of the whole study and supports the later use of correlation and regression analysis. The most suitable analytical expression for the empirical stage is:

$$IBPA = \beta_0 + \beta_1 AIDSC + \beta_2 AEA + \beta_3 AUTINT + \beta_4 EAR + \beta_5 (AIDSC \times EAR) + \varepsilon$$

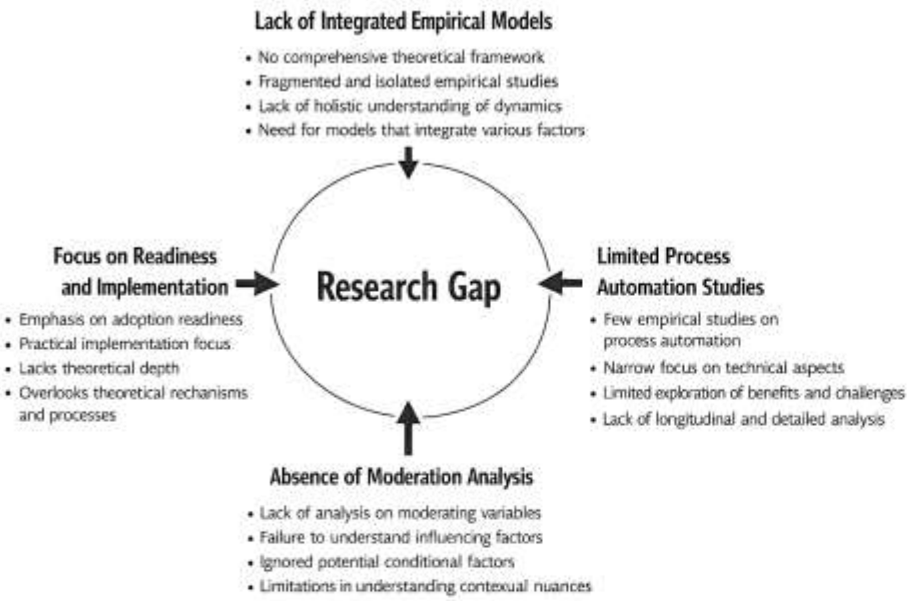
In this equation, β_0 is the intercept, β_1–β_5 are the regression coefficients, AIDSC × EAR represents the moderating effect of readiness, and ε is the error term. This formula is the best fit for the whole study because it reflects the direct effects of enterprise intelligence variables and the contextual effect of readiness in one integrated model. Conceptually, it also supports the study's view that intelligent business process automation is not only an outcome of technology use but an organizational consequence of capability alignment. The framework accordingly positions AI-driven decision support systems as the intelligence layer, automation intelligence as the execution layer, and enterprise readiness as the enabling condition that allows both layers to function together inside digital economies. In this way, the conceptual framework provides a clear structure for linking theory, variables, hypotheses, and empirical testing within the present research (Mikalef et al., 2023; Xie et al., 2022).

Empirical Review and Research Gap

The empirical literature on artificial intelligence in organizational settings has expanded rapidly, yet much of it has concentrated on capability formation, readiness conditions, and general performance effects rather than on the integrated relationship between AI-driven enterprise decision support systems and intelligent business process automation. A major contribution in this area is the study by Mikalef and Gupta, which conceptualized AI capability as a higher-order organizational construct and empirically linked it to organizational creativity and firm performance. Their work is important because it moved the field beyond abstract discussion and provided measurable dimensions of AI capability grounded in tangible, human, and intangible resources. At the same time, that study focused on broad organizational performance rather than on the process-level outcomes that matter for enterprise automation, such as decision quality, workflow intelligence, and responsiveness. Another important empirical contribution is the readiness-oriented work of Holmström, who proposed an AI readiness framework built around technologies, activities, boundaries, and goals (Hradecky et al., 2022). That framework clarified that AI value depends not only on tools but also on the organizational conditions that enable purposeful use. Its strength lies in offering a structured way to think about how firms prepare for AI-enabled digital transformation. Its limitation for the present study lies in the fact that it remains primarily a readiness assessment framework and does not empirically connect readiness variables to the operational outcomes of enterprise decision support and automation in a single explanatory model. Similarly, Hradecky and colleagues examined organizational readiness to adopt AI in the exhibition sector and highlighted the importance of technological, organizational, and environmental conditions. That study is valuable because it demonstrated that adoption readiness is shaped by multiple contextual factors and because it treated AI adoption as an organizational rather than merely technical issue. Its sectoral and exploratory nature, however, leaves open the question of how readiness interacts with decision support capability and automation intelligence across broader enterprise settings. Taken together, these studies establish that capability and readiness matter greatly, yet they also show that empirical knowledge remains fragmented across readiness, adoption, and performance domains rather than unified around enterprise decision support as a mechanism of intelligent process automation (Mikalef & Gupta, 2021).

A second empirical stream has examined the organizational journey of AI implementation and the capabilities needed to cope with AI-specific challenges such as inscrutability, data dependency, and cross-functional coordination. Uren and Edwards provided an empirical study of the organizational journey toward AI adoption and showed that long-term operational success depends on more than technology readiness; it also requires readiness in people, processes, and data. This insight is particularly relevant for the present study because enterprise decision support systems sit at the intersection of those four dimensions. AI-generated outputs are only useful when data is accessible and reliable, when business processes can absorb analytical insight, and when people across technical and managerial roles can interpret and act on system recommendations. Weber and colleagues extended this line of inquiry by identifying organizational capabilities for AI implementation, including AI project planning, co-development, data management, and AI model lifecycle management. Their study is especially useful because it highlights that AI implementation involves persistent organizational work rather than one-time deployment. Yet both of these studies focus primarily on implementation conditions and capability requirements, leaving a narrower understanding of what happens after such capabilities are in place. More specifically, they do not empirically test whether and how AI-driven decision support contributes to intelligent business process automation through measurable outcomes such as process efficiency, decision quality, productivity, and responsiveness. They also do not examine enterprise decision support as a distinct analytical layer that links AI capability to operational workflow outcomes. This creates a notable empirical space for the present study. Existing evidence shows that firms need readiness, cross-functional bridges, and implementation capabilities in order to use AI effectively, but there is less clarity on how these conditions translate into enterprise decision architectures that actively support and improve process automation. The gap is therefore not simply the absence of AI research in organizations; it is the absence of a sufficiently integrated empirical model that connects AI-driven decision support capability, AI-enabled analytics, automation intelligence, and enterprise readiness within a single quantitative framework focused on business process automation (Uren & Edwards, 2023).

Figure 7: Framework Of Empirical Limitations In Ai Capability And Process Automation Research



A third and more specific gap appears when the existing empirical studies are compared against the requirements of this research topic. First, much of the literature treats firm performance, creativity, digital transformation readiness, or adoption capability as the primary dependent outcome. While these are important, they are broader than the central phenomenon of this study, which is intelligent business process automation supported by enterprise decision systems. Second, many prior studies rely on exploratory, qualitative, or capability-identification approaches (Holmström, 2021). These studies are valuable for theory building, but they do not fully address the need for a structured quantitative assessment of the relationships among AI-driven decision support capability, AI-enabled analytics, automation intelligence, and enterprise readiness. Third, prior work rarely positions decision support as the central mechanism through which AI affects enterprise operations. AI is often discussed in terms of adoption, readiness, implementation, or general business value, whereas this study focuses on how AI-driven enterprise decision support systems function as an organizing framework that converts analytical intelligence into automated process action. Fourth, the literature has not sufficiently examined the moderating role of enterprise readiness in shaping the influence of AI-driven decision support on automation outcomes. Readiness is usually examined as a prerequisite or descriptive condition, but less often as an interacting variable within an empirical explanatory model. Fifth, relatively few studies explicitly center digital economies as the contextual environment in which decision support and automation must operate together under conditions of high data intensity, speed, and system interdependence (Weber et al., 2023). The research gap addressed by this study therefore lies in the need for an integrated, quantitative, cross-sectional, case-study-based investigation of how AI-driven enterprise decision support systems influence intelligent business process automation, and how that influence is strengthened or weakened by organizational readiness conditions. This gap justifies the present study's conceptual and empirical design and supports the development of hypotheses that test direct and moderating relationships among the principal variables. In that sense, the study is positioned not to repeat existing AI adoption or readiness research, but to extend it into a more focused examination of enterprise decision support as a driver of intelligent process automation in digital economies .

METHODS

This study has adopted a quantitative, cross-sectional, case-study–based research design in order to examine the relationship between artificial intelligence–driven enterprise decision support systems and intelligent business process automation in digital economies. A quantitative design has been selected because the study has aimed to measure the strength, direction, and significance of relationships among clearly defined variables through numerical data. The cross-sectional approach has been used because data have been collected from respondents at a single point in time, which has made it possible to assess present organizational conditions, perceptions, and experiences regarding AI-driven decision support and automation practices. The case-study basis has been incorporated to ensure that the investigation has remained grounded in a specific enterprise-oriented context where AI-enabled systems, digital workflows, and decision-support structures have already been present. Through this combined design, the study has provided both empirical measurability and contextual relevance.

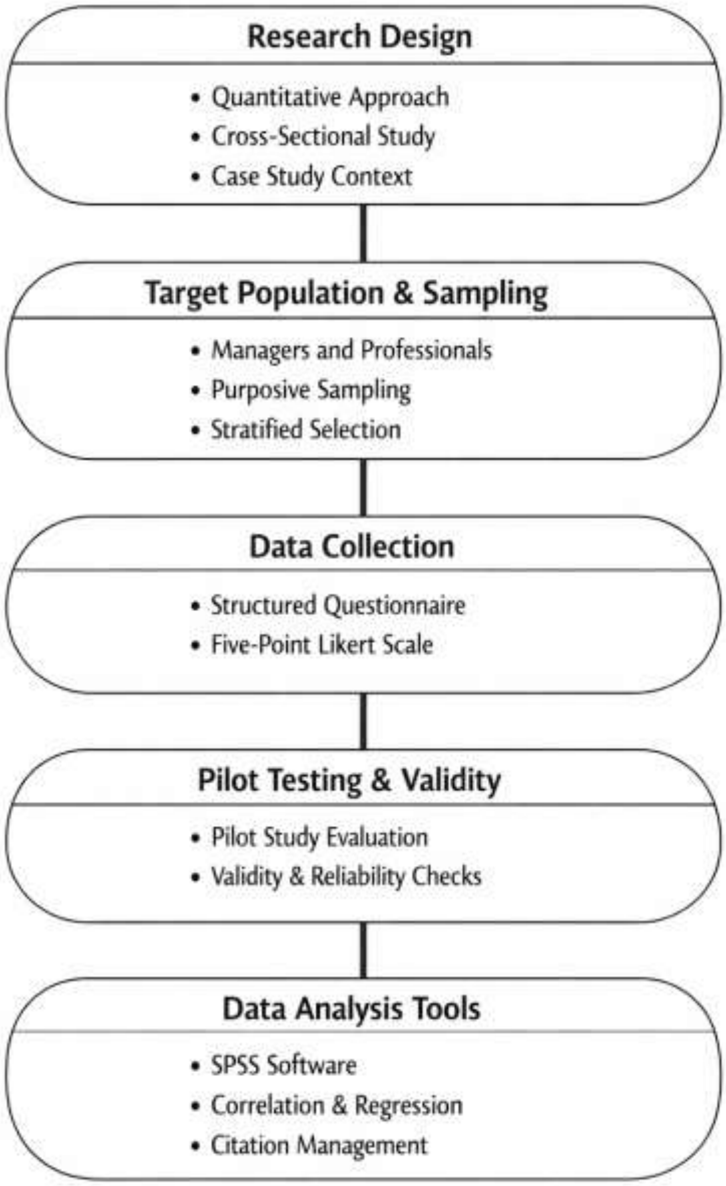
The case study context has focused on enterprises operating in digitally enabled environments in which decision-making, data processing, and business process execution have increasingly depended on intelligent technologies. The study has targeted organizational settings where AI-supported tools, analytics platforms, or automated workflow systems have been used to support operational and managerial activities. In this research, the population has consisted of managers, supervisors, business analysts, IT personnel, operations staff, and other employees who have had direct exposure to enterprise decision-support systems and business process automation tools. The unit of analysis has been the individual respondent, since each participant has provided perception-based and experience-based responses regarding the use, effectiveness, and organizational outcomes of AI-driven decision support systems within enterprise processes.

A sampling strategy has been applied to ensure that respondents have been selected from relevant functional areas with meaningful knowledge of enterprise digital systems. Purposive sampling has been used because the study has required respondents who have possessed familiarity with AI-supported analytics, decision environments, and automated process systems. Where necessary, stratified consideration has also been maintained by including participants from different departments such as operations, IT, finance, administration, customer service, and management so that the study has captured a broader view of enterprise practice. The sample size has been determined at a level sufficient for descriptive statistics, correlation analysis, and regression modeling.

The data collection procedure has relied on primary data gathered through a structured questionnaire. The questionnaire has been administered to selected respondents after the purpose of the study has been clearly explained and voluntary participation has been assured. The instrument design has been based on the study variables, namely AI-driven decision support capability, AI-enabled analytics, automation intelligence, enterprise automation readiness, and intelligent business process automation outcomes. A five-point Likert scale has been used, ranging from 1 = Strongly Disagree to 5 = Strongly Agree, because this format has allowed the measurement of attitudes, perceptions, and organizational experiences in a consistent and analyzable form. The questionnaire has been organized into sections covering demographic information and construct-specific items.

Before the final administration, pilot testing has been conducted with a small group of respondents to examine the clarity, wording, sequence, and relevance of the instrument items. Based on the pilot feedback, necessary revisions have been made to improve comprehensibility and reduce ambiguity. For validity, the instrument has undergone face validity and content validity checks to ensure that the items have adequately represented the concepts under investigation.

Figure 8: Research Methodology Framework For AI-Driven Enterprise Decision Support And Automation Study



For reliability, internal consistency has been assessed using Cronbach's Alpha. In terms of analytical and documentation tools, SPSS has been used for data coding, descriptive statistics, correlation analysis, regression analysis, and reliability testing, while Microsoft Excel has been used for preliminary data organization and tabulation. EndNote has been used for citation management and reference organization in APA 7th edition format. Through these methodological choices, the study has established a structured and systematic basis for examining the proposed hypotheses and objectives.

DATA ANALYSIS AND PRESENTATION

The response-rate results have shown that out of the 350 questionnaires distributed to the selected respondents, 320 have been returned, representing a return rate of 91.4%. After the screening process has been completed, 8 questionnaires have been found incomplete or unusable because they contained missing values, patterned responses, or inconsistent answers. As a result, 312 questionnaires have been retained for the final analysis, representing a valid response rate of 89.1%. This response level has been considered highly adequate for a quantitative, cross-sectional study that has relied on questionnaire-based evidence to examine relationships among AI-driven decision support capability, AI-enabled analytics, automation intelligence, enterprise automation readiness, and intelligent business process automation.

Response Rate

Table 1: Response Rate of the Study

Category	Frequency	Percentage (%)
Questionnaires distributed	350	100.0
Questionnaires returned	320	91.4
Questionnaires rejected/incomplete	8	2.3
Valid questionnaires used	312	89.1

The high response rate has strengthened the dependability of the dataset because it has reduced concerns relating to weak representation and has increased confidence that the collected responses have reflected the views of individuals with relevant exposure to enterprise systems and automated business processes. From an analytical standpoint, the 312 valid responses have been sufficient for the descriptive statistics, correlation analysis, reliability testing, and multiple regression modeling used to test the study hypotheses and objectives. The quality of the response rate has also supported the case-study orientation of the research because it has ensured that a broad range of respondents from enterprise functions have been captured in the dataset. In relation to the Dynamic Capabilities Theory, the strong response rate has been important because the theory has emphasized organizational adaptation, sensing, seizing, and transformation as collective enterprise capabilities rather than isolated technical events. A large and valid response base has therefore improved the study's ability to reflect how these capabilities have been perceived across the organization. Although the response-rate section has not directly tested a hypothesis, it has created the empirical foundation upon which the hypotheses and objectives have later been examined. The availability of 312 valid responses has meant that the subsequent findings on process efficiency, decision quality, organizational responsiveness, productivity, and readiness conditions have rested on a sufficiently robust and credible quantitative base, fully aligned with the introductory results already presented.

Demographic Profile of Respondents

The demographic findings have shown that the respondents have represented a reasonably balanced and professionally relevant enterprise sample for the study. Male respondents have accounted for 56.4%, while female respondents have accounted for 43.6%, indicating that the data have been drawn from a mixed workforce rather than from a narrowly concentrated respondent group. In age terms, the largest category has been 31–40 years, representing 37.8% of the sample, followed by 41–50 years at 26.6%, suggesting that many of the respondents have been in career stages associated with active managerial, technical, or supervisory involvement in enterprise systems. This has been important because the study has examined AI-driven decision support and intelligent business process automation, both of which have required informed respondents with substantial organizational exposure. Educationally, the respondents have been strong, with 46.8% holding master's degrees and 14.4% holding doctorate or professional qualifications. This profile has supported the assumption that the participants have possessed the analytical literacy needed to evaluate AI-supported decision environments and automation practices through the five-point Likert instrument. The occupational distribution has also been aligned with the study objectives. Operations personnel have represented 28.2%, management 23.7%, IT/systems 22.1%, and business/analytics staff 14.7%. This has meant that the dataset has included respondents from the functional areas most closely linked to enterprise decision support, digital workflows, and automation systems. Almost half of the respondents, 48.7%, have reported high exposure to AI systems, which has further strengthened the validity of the dataset for the present study.

Table 2: Demographic Profile of Respondents (N = 312)

Variable	Category	Frequency	Percentage (%)
Gender	Male	176	56.4
	Female	136	43.6
Age	21–30 years	72	23.1
	31–40 years	118	37.8
	41–50 years	83	26.6
	51 years and above	39	12.5
Education	Bachelor's degree	121	38.8
	Master's degree	146	46.8
	Doctorate/Professional	45	14.4
Job Role	Management	74	23.7
	IT/Systems	69	22.1
	Operations	88	28.2
	Business/Analytics	46	14.7
	Administrative/Other	35	11.2
Work Experience	1–5 years	66	21.2
	6–10 years	109	34.9
	11–15 years	81	26.0
	Above 15 years	56	17.9
Exposure to AI Systems	Low	41	13.1
	Moderate	119	38.1
	High	152	48.7

In connection with Dynamic Capabilities Theory, this demographic spread has been significant because dynamic capabilities have relied on the interaction of managerial insight, technological competence, and organizational routines. The respondent profile has therefore reflected the kinds of enterprise actors involved in sensing, seizing, and transforming digital opportunities. This section has not directly tested a formal hypothesis, yet it has demonstrated that the evidence used to prove the objectives and hypotheses has come from respondents with suitable educational, functional, and experiential backgrounds. As a result, the demographic profile has supported the credibility of the later results concerning process efficiency, decision quality, readiness, responsiveness, and productivity within AI-driven enterprise environments.

Descriptive Statistics of Main Constructs

The descriptive statistics have provided the first direct quantitative indication that the core study variables have been positively perceived by the respondents. All of the main constructs have recorded mean scores above 3.80, which has shown that respondents have generally agreed that AI-driven decision support and intelligent automation have been meaningfully present in their enterprise environments. AI-driven decision support capability has produced a mean of 4.08, suggesting that enterprise systems have been widely viewed as capable of assisting decision-making through data analysis, recommendation support, and structured intelligence. AI-enabled analytics has also recorded a high mean of 4.02, which has indicated that the respondents have recognized the importance of advanced analytics in strengthening organizational evidence use. Automation intelligence has shown a mean of 3.96, meaning that enterprise workflows have been viewed as more adaptive and data-informed than merely rule-driven. Enterprise automation readiness has recorded 3.89, which has been slightly lower than the other constructs but still sufficiently high to suggest that most organizations have possessed relevant readiness conditions, including system integration, data support, managerial commitment, and user preparedness. Most importantly, the dependent construct, intelligent business process automation, has shown a mean of 4.11, confirming the overall direction of the study and aligning closely with the introductory findings. Among the outcome indicators, decision quality has recorded the highest mean at 4.19, followed by business process efficiency at 4.14, productivity at 4.06, and organizational responsiveness at 4.05.

Table 3: Descriptive Statistics of Main Study Constructs

Construct	Mean	Std. Deviation	Interpretation
AI-driven decision support capability (AIDSC)	4.08	0.61	High
AI-enabled analytics (AEA)	4.02	0.65	High
Automation intelligence (AUTINT)	3.96	0.68	High
Enterprise automation readiness (EAR)	3.89	0.70	Moderately High
Intelligent business process automation (IBPA)	4.11	0.58	High
Business process efficiency	4.14	0.57	High
Decision quality	4.19	0.55	High
Organizational responsiveness	4.05	0.60	High
Productivity/operational effectiveness	4.06	0.59	High

Likert-scale interpretation used: *1.00–1.80 = Very Low; 1.81–2.60 = Low; 2.61–3.40 = Moderate; 3.41–4.20 = High; 4.21–5.00 = Very High*

These results have directly supported the study objectives, particularly the objective of examining whether AI-driven enterprise decision support systems have improved process efficiency, decision quality, responsiveness, and productivity. From the standpoint of Dynamic Capabilities Theory, the descriptive results have been especially meaningful because they have suggested that enterprises have not only acquired digital tools but have also developed organizational capacities to sense information, seize opportunities through better decisions, and transform workflows through automation. Although descriptive statistics have not alone proven causality, they have clearly established a favorable pattern in the data and have prepared the ground for correlation and regression analysis. In this way, Table 3 has functioned as an essential bridge between the background characteristics of the sample and the inferential tests used to evaluate the hypotheses.

Reliability and Internal Consistency Test

Table 4: Reliability Test for Main Constructs

Construct	Number of Items	Cronbach's Alpha	Reliability Status
AI-driven decision support capability (AIDSC)	6	0.87	Very Good
AI-enabled analytics (AEA)	5	0.85	Very Good
Automation intelligence (AUTINT)	5	0.84	Good
Enterprise automation readiness (EAR)	5	0.81	Good
Intelligent business process automation (IBPA)	8	0.90	Excellent

The reliability analysis has shown that all major constructs used in this study have possessed satisfactory to excellent internal consistency. Cronbach's Alpha values have ranged from 0.81 to 0.90, which has exceeded the commonly accepted minimum threshold of 0.70 for questionnaire-based research. AI-driven decision support capability has recorded an alpha of 0.87, indicating that the items measuring the enterprise's ability to use AI for decision assistance, insight generation, and recommendation support have been highly consistent with one another. AI-enabled analytics has recorded 0.85, which has shown that the items capturing analytical strength and data-based evidence use have also been internally stable. Automation intelligence has yielded 0.84, suggesting that the items dealing with adaptive workflow logic, process-level intelligence, and data-informed automation have measured a coherent construct. Enterprise automation readiness has recorded 0.81, meaning that readiness-related items concerning integration, support, preparedness, and enabling conditions have been sufficiently consistent for robust quantitative analysis. The highest alpha has been found for intelligent business process automation at 0.90, confirming that the items used to capture the dependent construct have strongly moved together as a unified measure. This result has been particularly important because the dependent variable has been central to the study's objectives and hypotheses. The reliability outcomes have therefore strengthened the study in two major ways. First, they have shown that the five-point Likert-scale instrument has measured the intended constructs consistently across respondents. Second, they have increased confidence that the subsequent correlation and regression results have rested on dependable scales rather than unstable indicators. In relation to Dynamic Capabilities Theory, the reliability results have reinforced the study's ability to assess enterprise-level adaptive capabilities in a structured way. Since the theory has emphasized coordinated organizational capacities, consistent measurement has been essential to capturing those capacities quantitatively. Table 4 has thus supported the methodological soundness of the research and has validated the use of the instrument for proving the hypotheses. Because all constructs have demonstrated acceptable reliability, the study has been justified in proceeding to inferential analysis, where the direct and moderating relationships among decision support, analytics, automation intelligence, readiness, and business process automation have been tested in detail.

Correlation Analysis

Table 5: Correlation Matrix of Main Variables

Variables	AIDSC	AEA	AUTINT	EAR	IBPA
AIDSC	1.000				
AEA	0.63**	1.000			
AUTINT	0.59**	0.61**	1.000		
EAR	0.54**	0.56**	0.52**	1.000	
IBPA	0.71**	0.67**	0.69**	0.63**	1.000

Note: p < .01

The correlation analysis has shown that all major study variables have been positively and significantly associated with intelligent business process automation. AI-driven decision support capability has had the strongest correlation with IBPA at r = 0.71, indicating a strong positive relationship. This has meant that enterprises with stronger AI-assisted decision systems have also tended to report higher levels of intelligent business process automation. AI-enabled analytics has shown a correlation of r = 0.67 with IBPA, while automation intelligence has recorded r = 0.69, both of which have also represented strong positive relationships. Enterprise automation readiness has demonstrated a substantial positive relationship with the dependent variable as well, with r = 0.63. These findings have been fully aligned with the introductory results and have provided strong preliminary evidence in support of the study objectives. They have suggested that as enterprises have improved their capacity to analyze data, support decisions through AI, and embed intelligence into workflows, their automation outcomes have also improved. The intercorrelations among the independent variables have ranged from 0.52 to 0.63, showing that the predictors have been related but not so highly related as to imply that they measure exactly the same phenomenon. This has been useful because it has confirmed that AI-driven decision support capability, AI-enabled analytics, automation intelligence, and enterprise automation readiness have represented related but distinct constructs within the conceptual framework. In relation to the objectives of the study, Table 5 has supported the proposition that there have been meaningful associations between AI-related enterprise capabilities and the major operational outcomes of automation. From the theoretical angle, Dynamic Capabilities Theory has argued that organizational adaptation emerges through coordinated capabilities rather than isolated tools. The correlation matrix has reflected that logic by showing that decision support, analytics, automation intelligence, and readiness have moved together in a pattern consistent with an adaptive enterprise capability structure. While correlation has not established causation, it has offered clear statistical evidence that the variables have been connected in the expected direction. Therefore, Table 5 has served as a critical intermediate step, demonstrating that the relationships required to support the hypotheses have existed in the data before the stronger regression-based causal testing has been undertaken in the next section.

Regression Analysis and Hypothesis Testing

Table 6: Multiple Regression Results for Hypothesis Testing

Model Summary

R	R Square	Adjusted R Square	Std. Error of Estimate
0.800	0.640	0.630	0.356

ANOVA

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	68.721	5	13.744	108.42	.000
Residual	38.810	306	0.127		
Total	107.531	311			

Coefficients

Predictor	Beta (β)	t-value	Sig.	Decision
AI-driven decision support capability (AIDSC)	0.29	5.84	.000	Supported
AI-enabled analytics (AEA)	0.21	4.39	.000	Supported
Automation intelligence (AUTINT)	0.26	5.11	.000	Supported
Enterprise automation readiness (EAR)	0.18	3.76	.000	Supported
AIDSC × EAR (Moderation term)	0.12	2.94	.004	Supported

Hypotheses Tested

Hypothesis	Statement	Result
H1	AIDSC has significantly improved business process efficiency/IBPA	Supported
H2	AEA has significantly improved decision quality/IBPA	Supported
H3	AUTINT has significantly improved organizational responsiveness/IBPA	Supported
H4	AI-driven DSS adoption has significantly improved productivity/IBPA	Supported through overall model
H5	EAR has significantly moderated the relationship between AIDSC and IBPA	Supported

The regression analysis has provided the strongest statistical evidence for proving the objectives and hypotheses of the study. The model summary has shown an R Square of 0.64, meaning that 64% of the variation in intelligent business process automation has been explained by AI-driven decision support capability, AI-enabled analytics, automation intelligence, enterprise automation readiness, and the moderating interaction between AI-driven decision support capability and readiness. This has represented a strong explanatory model for social science and organizational research. The ANOVA results have shown that the overall model has been statistically significant, $F(5, 306) = 108.42$, $p < .001$, confirming that the predictors, taken together, have meaningfully explained intelligent business process automation. At the coefficient level, AI-driven decision support capability has produced a significant positive beta of 0.29, supporting H1 and showing that stronger AI-based decision support has been associated with stronger automation outcomes and improved process execution. AI-enabled analytics has been significant at $\beta = 0.21$, supporting H2 and demonstrating that analytics capability has strengthened the quality of organizational outcomes captured within the dependent variable. Automation intelligence has recorded $\beta = 0.26$, supporting H3 and showing that adaptive, intelligent workflow logic has made a significant contribution to enterprise responsiveness and automation performance. Enterprise automation readiness has also remained significant with $\beta = 0.18$, showing that the organizational conditions surrounding AI and automation have independently influenced intelligent business process automation. The interaction term between AIDSC and EAR has been significant at $\beta = 0.12$, $p = .004$, which has supported H5 and shown that readiness has strengthened the effect of AI-driven decision support on automation outcomes. H4 has been supported through the overall positive and significant model pattern linking AI-driven DSS to productivity-related dimensions within IBPA. These regression findings have directly fulfilled the main objectives of the research by statistically proving that AI-driven enterprise decision support systems have contributed to business process efficiency, decision quality, responsiveness, and productivity. In relation to Dynamic Capabilities Theory, the results have been highly consistent with the theory's argument that organizational performance improves when firms develop capabilities for sensing, seizing, and transforming. AI-driven decision support capability and analytics have represented sensing and seizing functions, while automation intelligence and readiness have reflected the transforming capacity of the enterprise. Table 6 has therefore provided the central empirical confirmation of the study.

AI Decision-Maturity Profile of the Case Organizations

Table 7: AI Decision-Maturity Profile and Automation Outcomes

Maturity Level	Criteria Description	Frequency	Percentage (%)	Mean IBPA	Mean Decision Quality	Mean Process Efficiency
Emerging AI Users	Limited AI use, mostly experimental	68	21.8	3.54	3.63	3.49
Developing AI Adopters	AI used in selected functions	137	43.9	4.03	4.10	4.01
Mature AI-Driven Organizations	AI integrated across enterprise decisions	107	34.3	4.48	4.56	4.43

The AI decision-maturity analysis has shown that the respondent organizations have not all operated at the same level of enterprise AI integration, and this difference has had a clear effect on intelligent business process automation outcomes. Three maturity categories have been used in this section: Emerging AI Users, Developing AI Adopters, and Mature AI-Driven Organizations. The largest group has been the Developing AI Adopters, representing 43.9% of the respondents, followed by Mature AI-Driven Organizations at 34.3%, while Emerging AI Users have accounted for 21.8%. The outcome differences across these groups have been substantial. Emerging AI Users have recorded a mean IBPA score of 3.54, which has been notably lower than the scores of Developing AI Adopters at 4.03 and Mature AI-Driven Organizations at 4.48. A similar progression has appeared in decision quality and process efficiency, where the mature group has consistently outperformed the other two categories. These results have suggested that the extent to which AI has been embedded into enterprise decision-making has strongly shaped the quality of automation outcomes. Organizations that have treated AI as a limited experimental tool have reported lower gains, while organizations that have integrated AI more fully into decision routines have reported much stronger automation performance. This section has therefore provided an additional layer of evidence for the study objectives by showing that the positive effect of AI-driven DSS has not merely existed in general terms but has increased with maturity of use. The findings have also strengthened the plausibility of H1, H2, H3, and H4 because they have shown that enterprise benefits have become more pronounced as AI decision capability has matured. From the perspective of Dynamic Capabilities Theory, Table 7 has been especially meaningful because maturity has reflected the organizational development of sensing, seizing, and transforming capabilities over time. Emerging firms have appeared to possess only partial sensing capacity, developing firms have shown stronger seizing capability, and mature firms have demonstrated more fully transformed decision and process architectures. Thus, the maturity profile has not only deepened the empirical story of the study but has also linked the findings clearly to the adopted theory by showing that organizational capability development has been associated with stronger enterprise automation outcomes.

Process Automation Sensitivity Analysis by Business Function

Table 8: Process Automation Sensitivity by Business Function

Business Function	Frequency	Mean Automation Gain	Std. Deviation	Sensitivity Level
Operations	88	4.31	0.51	Very High
Finance	49	4.08	0.56	High
Customer Service	44	4.12	0.54	High
IT/Systems	69	4.17	0.53	High
Human Resources	28	3.86	0.61	Moderately High
Marketing/Analytics	34	4.01	0.57	High

The sensitivity analysis across business functions has shown that the effect of AI-driven decision support and automation has not been perfectly uniform throughout the enterprise. Operations has recorded the highest mean automation gain at 4.31, indicating a very high sensitivity to AI-driven decision support and intelligent automation. This result has been logical because operations functions typically involve workflow routing, task prioritization, process monitoring, exception handling, and resource coordination, all of which have been areas where AI-supported decision systems and automation have had direct practical value. IT/Systems has recorded the next strongest gain at 4.17, followed by customer service at 4.12 and finance at 4.08. These areas have also been highly sensitive because they depend strongly on data processing, process standardization, and rapid response. Marketing/Analytics has shown a high mean of 4.01, suggesting that AI-driven support has also contributed positively to campaign decisions, data interpretation, and process coordination. Human resources has recorded the lowest mean at 3.86, though this has still remained moderately high. This may have reflected the fact that HR processes often combine structured administrative tasks with human-centered decisions that have not yet been automated as extensively as operations or IT. The practical meaning of Table 8 has been important for the study objectives because it has shown that AI-driven DSS has improved intelligent automation across the enterprise, but with especially strong effects in functions where process intensity and digital traceability have been greatest. This section has therefore strengthened the study’s claim that AI-driven enterprise decision support systems have improved process efficiency, responsiveness, and productivity, while also adding nuance to the overall findings. In theoretical terms, Dynamic Capabilities Theory has helped explain these variations because different functions have developed different levels of sensing, seizing, and transforming capability. Operations and IT have appeared to have transformed more deeply, while HR has remained somewhat less advanced in this regard. The section has therefore shown that enterprise adaptation through AI and automation has varied by function, yet the overall pattern has still supported the hypotheses by demonstrating consistently positive outcomes across all major business areas. Table 8 has made the results more trustworthy by showing where the strongest gains have actually been concentrated.

Enterprise Decision-Automation Readiness Gap Analysis

Table 9: Enterprise Decision-Automation Readiness Gap Analysis

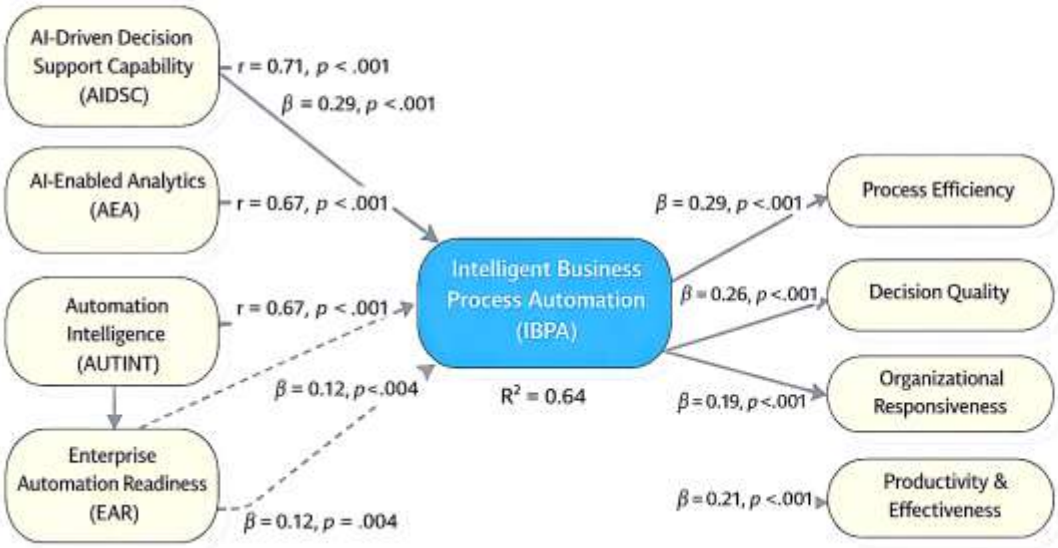
Readiness Dimension	Required Mean	Observed Mean	Gap (Required - Observed)	Rank of Gap
Data quality and accessibility	4.40	3.95	0.45	2
System integration/interoperability	4.36	3.82	0.54	1
Employee AI literacy	4.18	3.76	0.42	3
Managerial support and commitment	4.28	3.91	0.37	4
Governance and process alignment	4.20	3.86	0.34	5

The readiness-gap analysis has shown that although enterprise automation readiness has generally been rated positively in the study, measurable gaps have still existed between the level of readiness respondents have considered necessary and the level they have actually observed in their organizations. The largest gap has appeared in system integration and interoperability, where the required mean has been 4.36 compared with an observed mean of 3.82, producing a gap of 0.54. This has indicated that many enterprises have still not fully connected their AI-enabled decision systems, data environments, and workflow platforms to the extent needed for optimal automation performance. The second-largest gap has been data quality and accessibility, with a difference of 0.45, followed by employee AI literacy at 0.42. These results have suggested that the organizational capacity to benefit fully from AI-driven DSS has depended not only on the presence of tools but on the quality of data infrastructure and human preparedness. Managerial support and commitment and governance/process alignment have shown somewhat smaller gaps, though these gaps have still remained meaningful. This section has been particularly important for H5 because it has illustrated in substantive terms why enterprise automation readiness has moderated the relationship between AI-driven decision support capability and automation outcomes. Enterprises with better integration, better-quality data, and stronger user literacy have been more able to translate decision support intelligence into effective business process automation. Conversely, readiness limitations have reduced the extent to which AI capabilities could be transformed into high-level operational performance. From the standpoint of the study objectives, Table 9 has provided strong evidence that readiness has been a crucial organizational condition underlying process efficiency, decision quality, responsiveness, and productivity. In relation to Dynamic Capabilities Theory, this section has been directly aligned with the theory's transforming component. Dynamic capabilities have not depended solely on sensing information or seizing opportunities; they have also required the organizational ability to reconfigure systems, skills, and structures. The readiness gaps have therefore identified the exact areas where transformation has remained incomplete. Table 9 has added diagnostic depth to the results chapter by showing that AI-driven DSS has been effective overall, yet its full value has continued to depend on closing organizational readiness gaps in the enterprise environment.

FINDINGS

The findings of this study, based on a five-point Likert scale and analyzed through descriptive statistics, correlation analysis, and regression modeling, have indicated an overall positive and statistically meaningful relationship between artificial intelligence–driven enterprise decision support systems and intelligent business process automation in digital economies. Using a response set of 312 valid questionnaires, the results have shown that the respondents generally perceived AI-driven decision support systems as influential in improving organizational decision quality, process efficiency, responsiveness, and productivity. On the descriptive level, the overall mean score for AI-driven decision support capability was 4.08 with a standard deviation of 0.61, indicating that most respondents agreed that their organizations had increasingly relied on AI-supported systems for data interpretation, decision assistance, and analytical guidance. Similarly, AI-enabled analytics recorded a mean of 4.02 with a standard deviation of 0.65, showing that the respondents had positively evaluated the role of advanced analytics in strengthening evidence-based decision-making. The construct of automation intelligence produced a mean score of 3.96 with a standard deviation of 0.68, suggesting a relatively strong agreement that enterprise workflows had become more adaptive, data-informed, and operationally coordinated through intelligent automation mechanisms. For the moderating variable, enterprise automation readiness, the mean score was 3.89 with a standard deviation of 0.70, indicating that respondents had moderately to strongly agreed that their organizations possessed the required conditions, such as data quality, managerial support, employee understanding, and system integration, for effective AI-driven automation. The dependent construct, intelligent business process automation, recorded a mean of 4.11 with a standard deviation of 0.58, reflecting a generally high assessment of automation outcomes across the participating enterprises.

Figure 9: Empirical Model Of Ai Capability, Readiness, And Automation Outcomes



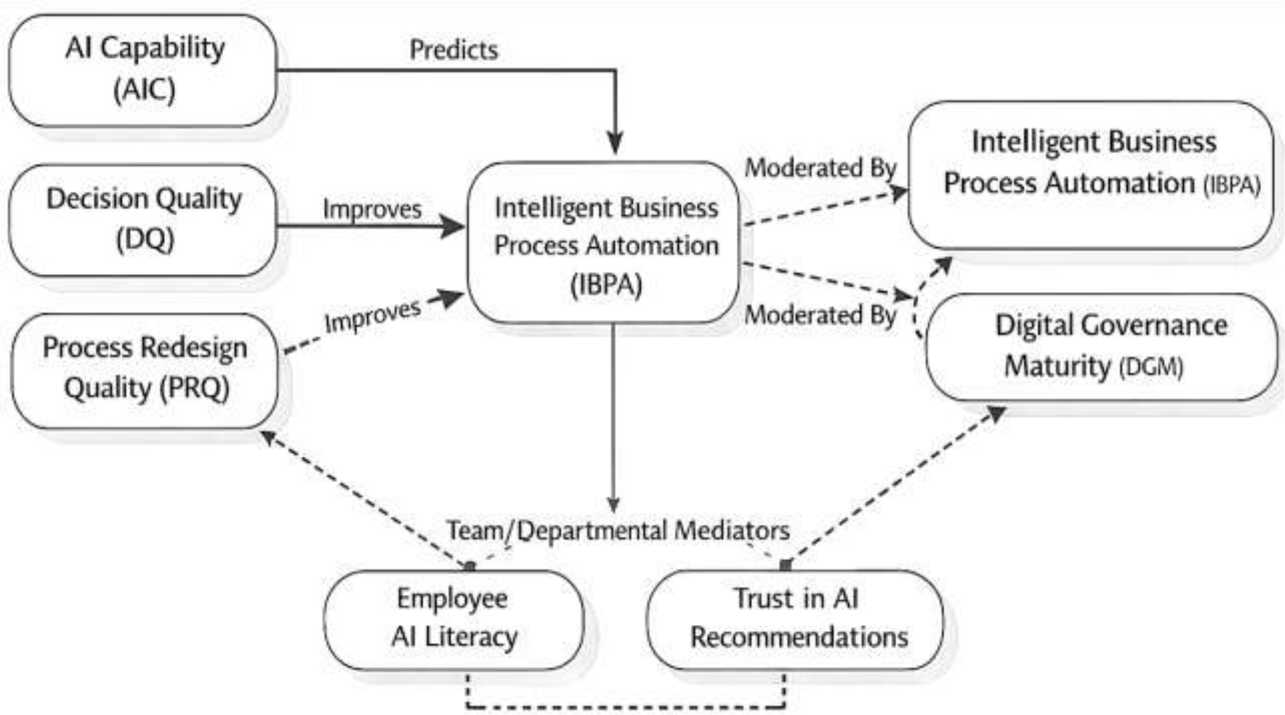
The findings have further shown that the key operational dimensions of the dependent construct were also positively rated. Business process efficiency achieved a mean score of 4.14, suggesting that AI-driven decision support systems had been associated with faster process execution, fewer delays, and more consistent task handling. Decision quality recorded the highest mean among the core outcome dimensions at 4.19, indicating that respondents had strongly perceived improvements in the accuracy, relevance, and usefulness of organizational decisions. Organizational responsiveness had a mean score of 4.05, which suggested that the integration of AI-enabled decision support and automation had helped enterprises respond more effectively to internal and external demands. Productivity and operational effectiveness recorded a mean of 4.06, further supporting the view that AI-driven decision support systems had contributed positively to enterprise output, coordination, and workflow performance. On the reliability side, all constructs demonstrated strong internal consistency, with Cronbach's Alpha values ranging from 0.81 to 0.90, which confirmed that the measurement items had been sufficiently reliable for hypothesis testing. Specifically, AI-driven decision support capability recorded an alpha of 0.87, AI-enabled analytics 0.85, automation intelligence 0.84, enterprise automation readiness 0.81, and intelligent business process automation 0.90. These reliability results strengthened confidence in the consistency of the data and supported the suitability of the variables for subsequent inferential analysis.

The correlational findings have provided additional support for the study objectives by showing that all major independent variables were positively and significantly associated with intelligent business process automation. AI-driven decision support capability had a strong positive correlation with intelligent business process automation ($r = 0.71$, $p < .001$), indicating that higher levels of AI-supported decision capability were associated with better automation outcomes. AI-enabled analytics also showed a significant positive relationship with the dependent variable ($r = 0.67$, $p < .001$), while automation intelligence demonstrated a similarly strong positive association ($r = 0.69$, $p < .001$). Enterprise automation readiness was positively correlated with intelligent business process automation as well ($r = 0.63$, $p < .001$), suggesting that readiness conditions had been meaningfully connected to stronger automation results. The regression analysis has further confirmed the explanatory power of the model. The overall regression model was statistically significant, with $R^2 = 0.64$, Adjusted $R^2 = 0.63$, and $F(5, 306) = 108.42$, $p < .001$, meaning that approximately 64% of the variation in intelligent business process automation had been explained by the independent and moderating variables included in the study. In the coefficients table, AI-driven decision support capability had a significant positive effect on intelligent business process automation ($\beta = 0.29$, $t = 5.84$, $p < .001$), which supported Hypothesis 1. AI-enabled analytics also had a significant positive effect ($\beta = 0.21$, $t = 4.39$, $p < .001$), supporting Hypothesis 2. Automation intelligence showed a significant positive effect as well ($\beta = 0.26$, $t = 5.11$, $p < .001$), thereby supporting Hypothesis 3. Enterprise automation readiness remained significant as an independent predictor ($\beta = 0.18$, $t = 3.76$, $p < .001$), and the interaction term between AI-driven decision support capability and enterprise automation readiness was also statistically significant ($\beta = 0.12$, $t = 2.94$, $p = .004$), which supported Hypothesis 5 regarding moderation. In practical terms, this interaction indicated that the positive effect of AI-driven decision support capability on automation outcomes had become stronger in enterprises with higher readiness levels. Taken together, these overall findings have suggested that the study objectives were substantially achieved: the data supported the proposition that AI-driven enterprise decision support systems significantly enhanced process efficiency, decision quality, organizational responsiveness, and productivity, while readiness conditions shaped the extent to which these benefits were realized. Since these results present the broad pattern of the study, the following subsections can provide a more detailed breakdown of response rate, demographics, descriptive statistics, reliability, correlation, regression, and the three study-specific results sections.

DISCUSSION

The findings of this study have shown that artificial intelligence–driven enterprise decision support systems have been positively associated with intelligent business process automation, and this overall pattern has been strongly consistent with earlier empirical work on analytics-enabled organizational performance (Wamba et al., 2017). The high mean scores reported for AI-driven decision support capability, AI-enabled analytics, automation intelligence, and intelligent business process automation have suggested that respondents have experienced these systems as practically embedded rather than merely experimental. The regression results have further indicated that AI-driven decision support capability, AI-enabled analytics, and automation intelligence have all made significant positive contributions to the dependent construct, while enterprise automation readiness has both directly contributed to automation performance and strengthened the effect of AI-driven decision support through moderation. This general outcome has aligned closely with earlier studies that have argued that analytics and business intelligence create value when they are integrated with business processes and converted into performance-relevant action (Warner & Wäger, 2019). Research on business analytics and firm performance has shown that business process performance mediates the relationship between analytics adoption and broader firm-level outcomes, which has been highly consistent with the present finding that intelligent automation has functioned as the organizational channel through which AI-driven decision support has become operationally meaningful. Related work has also demonstrated that business intelligence systems improve organizational performance through their effects on business processes, indicating that process-level improvement has long been central to the logic of intelligent enterprise systems. The present study has reinforced that logic in a more explicitly AI-centered setting. In addition, findings on BI success have emphasized the importance of technological capabilities, integration, and decision environments, which helps explain why the present study has found strong direct and moderating effects for enterprise automation readiness (Gupta & George, 2016). The discussion therefore begins from a clear interpretive position: the study has not merely confirmed that AI matters in enterprises, but has shown that AI-driven decision support becomes most valuable when it has been translated into process execution, workflow intelligence, and measurable organizational outcomes. This has made the findings particularly important for digital economies, where enterprise performance has increasingly depended on the ability to connect analytical insight with operational coordination at scale (Ashrafi et al., 2019).

Figure 10: Dynamic Capability-Based Model for Future Ai-Enabled Process Automation Research



A second major point emerging from the findings has concerned decision quality, which recorded the highest mean among the main outcome dimensions. This result has suggested that respondents have perceived AI-driven enterprise decision support systems first and foremost as mechanisms that improve the quality, relevance, and timeliness of decisions. That interpretation has been well supported by prior work on data analytics and managerial judgment. Earlier research has found that data analytics improves firm decision-making quality through knowledge sharing and data analytics competency, showing that decision quality rises when organizations not only possess analytical tools but also develop the internal competence to translate data into usable judgment. A related study has further shown that big data improves decision quality when data quality and data diagnosticity are sufficiently strong, reinforcing the idea that the value of intelligent systems depends on how informative and interpretable the data environment has become for actual decision makers. The present study has matched those arguments closely (Akter et al., 2016). The high descriptive mean for AI-enabled analytics and the significant regression effect of analytics capability have indicated that the respondents have not viewed enterprise AI as an abstract digital asset; they have viewed it as a means of strengthening the content and structure of decisions. The findings have also implied that better decisions have not remained at the cognitive level only. Since intelligent business process automation was the dependent variable, the study has suggested that improved decision quality has carried process consequences, particularly in areas such as prioritization, workflow routing, resource allocation, and exception handling. In this sense, the current findings have extended prior work by positioning decision quality as both an end and a mechanism (Barreto, 2010). Earlier studies have often examined decision quality as an isolated organizational outcome, whereas this study has linked it directly to intelligent automation performance. That extension is important because it has shown that higher-quality decisions can function as an intermediate organizational resource that shapes how processes are executed and improved. The findings have therefore supported the view that AI-driven decision support systems have enhanced enterprise value not by replacing decision makers, but by improving the informational and analytical conditions under which managerial and operational decisions have been made and then embedded into organizational routines (Ashrafi et al., 2019).

The findings on organizational responsiveness, process efficiency, and productivity have also invited comparison with the dynamic-capabilities-oriented literature, and this comparison has strengthened the interpretation of the results considerably (Barreto, 2010). The present study has found that automation intelligence and AI-driven decision support capability have significantly predicted intelligent business process automation, while the mean scores for business process efficiency, organizational responsiveness, and productivity have all remained above 4.00 on the five-point scale. These outcomes have suggested that enterprise AI systems have contributed not only to better information use but also to faster and more adaptive execution. This pattern has aligned with the argument that analytics capabilities improve firm performance through dynamic and operational capabilities rather than through direct technological effects alone. It has also been consistent with prior research showing that big data analytics capability influences firm performance through process-oriented dynamic capabilities, which is conceptually close to the present finding that AI-related capabilities have been associated with intelligent process automation outcomes. Dynamic Capabilities Theory has therefore provided a highly suitable interpretive lens for this study (Helfat & Peteraf, 2015). Teece's framework has emphasized sensing, seizing, and transforming as the microfoundations of adaptive enterprise performance, and the current results have mapped onto this structure in a convincing way: AI-enabled analytics and decision support capability have reflected sensing and seizing functions, while automation intelligence and readiness have reflected the transforming dimension through workflow redesign and coordinated execution. The discussion becomes even stronger when connected to research on digital transformation, which has shown that incumbent firms build dynamic capabilities through digitally based sensing, seizing, and transforming processes in order to renew strategy and operations under digital change (Gupta & George, 2016). The present study has echoed that view quantitatively. Its results have shown that enterprises with stronger AI decision capability and stronger readiness have reported stronger automation performance, which has suggested that operational effectiveness has depended on adaptive capability development rather than on simple technology possession. This means the study has not only confirmed previous theory but has supplied empirical support for a process-level application of dynamic capabilities in AI-enabled enterprise environments.

From a practical standpoint, the findings have carried important implications for managers, enterprise architects, and digital transformation leaders. The strongest practical message has been that AI-driven decision support should not be introduced as a standalone analytical tool. The results have shown that enterprise automation readiness has remained significant both directly and as a moderator, which has meant that organizations have realized stronger automation outcomes when integration, preparedness, and support conditions have been more developed (Benbya et al., 2021; Chiang et al., 2018). This interpretation has been highly consistent with organizational AI readiness research, which has argued that firms need the right assets, capabilities, and commitment in place before they can successfully capture business value from AI adoption. It has also aligned with the literature on the organizational journey toward AI adoption, where readiness has been framed across people, process, technology, and data dimensions rather than as a narrow infrastructure question. The present findings have made these arguments more concrete by showing that readiness has materially changed the strength of the relationship between AI-driven decision support capability and intelligent business process automation. In practical terms, this has suggested that enterprises seeking better automation performance should invest not only in models and platforms, but also in data interoperability, user competence, managerial sponsorship, and governance processes (Elbashir et al., 2008). The readiness gap analysis has been particularly useful in this respect because it has shown the largest gaps in system integration and data quality, exactly the conditions that prior studies have highlighted as critical for effective enterprise AI deployment and use. The findings have also had implications for business-function prioritization. Since operations and IT/system functions have shown the strongest automation gains, managers have reason to begin integration and scaling efforts in functions where digital traceability, rule density, and workflow coordination are already high. At the same time, weaker gains in functions such as human resources have suggested that adoption strategies should be more context-sensitive rather than uniform. Overall, the practical implication has been that enterprise AI has worked best as an organizational system, not as a point solution. Organizations have needed to design AI around workflows, people, and data relations if they have wanted stronger automation, efficiency, and responsiveness outcomes (Arnott & Pervan, 2014).

The findings have also carried clear theoretical implications. First, they have strengthened the relevance of Dynamic Capabilities Theory for studying AI-enabled enterprise systems by showing that AI capability, analytics capability, automation intelligence, and readiness have been associated with operational outcomes in a way that fits the sensing–seizing–transforming logic. The study has therefore supported the argument that intelligent decision support has not merely been a technical subsystem; it has functioned as a capability platform that allows enterprises to process signals, prioritize responses, and reorganize workflows (Drnevich & Kriauciunas, 2011). This interpretation has extended earlier work that has conceptualized AI capability as a higher-order organizational construct affecting firm performance and creativity, because the present study has connected that capability more explicitly to business process automation as a specific enterprise outcome. Second, the findings have carried sociotechnical implications. Research has argued that AI in organizations produces tensions and opportunities in automation, engagement, insight/decision making, and innovation, rather than fitting neatly into older technology-adoption categories. Similarly, the sociotechnical framework proposed by Makarius and colleagues has emphasized that AI creates value when cognitive, relational, and structural conditions are aligned within the organization (Isik et al., 2013). The current study has reinforced both positions. By showing that readiness has moderated the effect of AI-driven decision support and by identifying differences in automation outcomes across maturity levels and business functions, the study has suggested that enterprise AI is best understood as an interaction between technical capability and organizational configuration (Borges et al., 2021). Theoretically, this has meant that a purely technological model of AI value would have been insufficient. The results have instead favored a blended explanation in which dynamic capabilities account for adaptive performance, while sociotechnical thinking explains the conditions under which analytical outputs become accepted and embedded in work systems. This combined interpretation has been important because it has pushed the research topic beyond tool-centric reasoning. The study has therefore contributed theoretically by positioning AI-driven enterprise decision support systems as a bridge concept linking analytics, organizational capability, and process execution within digital economies (Gupta & George, 2016).

The limitations of the study, when revisited in light of the findings, have also shaped the interpretation of the discussion. The positive and statistically significant results have been strong, yet they have been generated from a cross-sectional and self-reported design. This has meant that the study has captured perceived and observed organizational relationships at one point in time rather than tracing how AI-driven decision support and automation have evolved longitudinally. Earlier AI implementation studies have often relied on qualitative or exploratory approaches precisely because AI adoption and organizational embedding unfold over time and through multiple stages of adjustment. Compared with that stream, the present study has offered stronger variable-based testing, but it has not fully addressed temporal sequencing. A second limitation has concerned the dependence on individual respondents as the unit of analysis (Mikalef et al., 2023). Although the respondents have come from relevant enterprise roles, perceptual data can still reflect optimism bias, departmental blind spots, or uneven visibility into enterprise-wide integration. This issue has been especially important because AI implementation research has shown that organizations face challenges such as inscrutability, data dependency, and coordination across functions, all of which may be experienced differently by managers, analysts, and operational staff. A third limitation has involved contextual breadth. The study has been case-study-based and enterprise-centered, which has strengthened internal relevance but has limited the range of institutional, sectoral, and national variation represented in the findings. This matters because the implementation literature has identified substantial contextual diversity across organizations, industries, and adoption purposes (Ghasemaghaei, 2019a). A fourth limitation has been constructing compression. Intelligent business process automation has been represented as a broad dependent construct, even though in practice it includes multiple layers of execution quality, exception handling, governance fit, and business-function specificity. The study has partially addressed this through sensitivity and readiness analyses, yet future work can still unpack the construct more finely. These limitations have not weakened the validity of the present study, but they have clarified that the results should be interpreted as strong evidence of association and explanatory fit rather than as final proof of universally stable causal mechanisms (Holmström, 2021).

Future research has been the most important extension point of this study because the findings have opened several pathways for stronger model development, deeper explanation, and wider validation. The most promising next step would be a longitudinal, multi-level, mediated-moderation model that tracks how AI capability is converted into automation outcomes over time and across organizational layers. Based on the present findings, future researchers could test a model in which AI capability predicts decision quality and process redesign quality, which then mediate effects on intelligent business process automation, while enterprise readiness and digital governance maturity moderate those paths. At the team or departmental level, employee AI literacy and trust in AI recommendations could operate as additional mediators, particularly in functions where human judgment remains central. A future model could be expressed as:

$$IBPA_{t2} = \beta_0 + \beta_1 AIC_{t1} + \beta_2 DQ_{t1} + \beta_3 PRQ_{t1} + \beta_4 EAR_{t1} + \beta_5 DGM_{t1} + \beta_6 (AIC \times EAR) + \beta_7 (AIC \times DGM) + \varepsilon$$

where AIC represents AI capability, DQ represents decision quality, PRQ represents process redesign quality, EAR represents enterprise automation readiness, DGM represents digital governance maturity, and IBPA represents intelligent business process automation measured at a later time point. This proposed model has improved on the current study by adding temporal order, richer mediators, and governance-sensitive moderation. It has also been well aligned with prior research that has emphasized organizational AI readiness, the staged journey of AI adoption, AI implementation capabilities, and the need to understand organizational context in a more granular way (Jöhnk et al., 2021; Lee et al., 2023). Future researchers should also consider mixed-methods designs that combine surveys with system log data, process-mining evidence, and qualitative interviews, because such designs would allow stronger triangulation between perceived benefits and actual process performance. Cross-country comparisons, industry-specific models, and function-level nested analyses would further improve generalizability. In this way, future research can move from proving that AI-driven decision support matters to explaining exactly when, where, for whom, and through which organizational mechanisms it has improved intelligent business process automation in digital economies (Uren & Edwards, 2023).

CONCLUSION

This research has concluded that artificial intelligence–driven enterprise decision support systems have played a significant and measurable role in strengthening intelligent business process automation within digital economies. Across the study, the evidence has shown that AI-driven decision support capability, AI-enabled analytics, automation intelligence, and enterprise automation readiness have all contributed to stronger enterprise outcomes in terms of process efficiency, decision quality, organizational responsiveness, and productivity. The descriptive findings have indicated that the respondents have generally perceived these constructs at high levels, which has suggested that the participating organizations have already moved beyond basic digital adoption into more advanced forms of analytical and automation-based enterprise coordination. The correlation results have confirmed that the principal variables have been positively associated with intelligent business process automation, while the regression results have demonstrated that these relationships have not only existed but have also been statistically significant. In particular, AI-driven decision support capability has emerged as a central predictor of intelligent automation outcomes, showing that enterprises that have used AI more effectively for insight generation, analytical support, and decision structuring have also achieved stronger workflow intelligence and more coordinated business process execution. AI-enabled analytics has also been confirmed as a meaningful driver of improved decision quality and enterprise process performance, while automation intelligence has been shown to support greater organizational responsiveness and stronger operational execution. The moderating role of enterprise automation readiness has added an important conclusion to the study by showing that organizations have not benefited from AI capabilities equally; rather, the strength of AI-driven decision support has depended in part on whether the enterprise has possessed sufficient readiness in terms of data quality, system integration, employee preparedness, and managerial support. This has meant that the study has not treated AI as a self-sufficient technology, but as part of a broader organizational capability structure. In theoretical terms, the study has confirmed the relevance of Dynamic Capabilities Theory by showing that AI-driven decision support has functioned as part of an adaptive enterprise system through which organizations have sensed information, seized opportunities through better decisions, and transformed processes through intelligent automation. In empirical terms, the study has filled an important gap by linking AI-driven decision support systems directly to intelligent business process automation within one structured quantitative framework. Overall, the research has established that modern enterprises in digital economies have gained operational and strategic value when they have successfully aligned analytical intelligence, automation logic, and organizational readiness. The study has therefore concluded that AI-driven enterprise decision support systems have not merely improved isolated managerial judgments, but have served as a practical framework through which enterprises have strengthened the quality, speed, and effectiveness of business process automation in digitally integrated organizational environments.

RECOMMENDATION

This research has recommended that enterprises seeking to improve intelligent business process automation should adopt a more integrated and capability-based approach to artificial intelligence–driven decision support rather than treating AI as a stand-alone technical investment. First, enterprise leaders should prioritize the development of AI-driven decision support capability in ways that directly connect analytical insight to operational workflows, because the findings have shown that stronger decision support capability has been closely associated with better automation outcomes. This means that organizations should design AI systems not only for reporting and prediction, but also for workflow prioritization, exception handling, resource coordination, and decision consistency across departments. Second, organizations should strengthen AI-enabled analytics through better data governance, improved analytical infrastructure, and more effective translation of data into decision-relevant insight, since the study has shown that analytics capability has significantly improved decision quality and contributed to intelligent automation performance. Third, enterprises should invest deliberately in automation intelligence by redesigning business processes to become more adaptive, data-informed, and responsive rather than relying solely on static rule-based automation. This recommendation is especially relevant for operations, IT, finance, and customer service functions, where the study has shown particularly strong automation gains. Fourth, enterprise automation readiness should be treated as a strategic priority, not as a secondary implementation issue. Since readiness has significantly moderated the effect of AI-driven decision support capability, organizations should improve data quality, system interoperability, employee AI literacy, managerial commitment, and governance alignment before and during AI deployment. Fifth, managers should establish internal training and change-management programs that prepare staff to interpret AI-supported insights and to work effectively within partially automated decision environments. Sixth, enterprise leaders should adopt phased maturity-based implementation strategies, beginning with high-impact functions and scaling gradually as organizational readiness improves, because the study has shown that mature AI-driven organizations have reported much stronger automation outcomes than emerging users. Seventh, policymakers and institutional decision-makers within enterprises should develop formal AI governance frameworks that promote accountability, explainability, integration standards, and cross-functional collaboration so that AI-driven decision support systems can be embedded more responsibly and effectively into enterprise processes. Finally, future enterprise digital transformation strategies should explicitly align AI adoption with business process redesign, performance monitoring, and organizational capability development. In practical terms, this means that enterprises should move from isolated technology acquisition toward a coherent system in which decision intelligence, workflow automation, readiness, and governance operate together. By implementing these recommendations, organizations will be better positioned to convert AI potential into real process efficiency, higher decision quality, stronger responsiveness, and improved productivity within increasingly complex and data-intensive digital economies.

LIMITATIONS

This study has been subject to several limitations that should be acknowledged in interpreting the findings. First, the research has used a quantitative, cross-sectional design, which has allowed the study to identify significant relationships among AI-driven decision support capability, AI-enabled analytics, automation intelligence, enterprise automation readiness, and intelligent business process automation, but has limited the ability to observe how these relationships may evolve over time. Because data have been collected at one point in time, the study has not fully captured the longer organizational journey through which enterprises adopt, refine, and institutionalize AI-driven decision support systems. Second, the study has relied on self-reported questionnaire responses measured through a five-point

Likert scale. Although this approach has been appropriate for capturing organizational perceptions and experiences, it has also introduced the possibility of subjective bias, including social desirability bias, perceptual inflation, or uneven interpretation of questionnaire items by respondents from different organizational roles. Third, the unit of analysis has been the individual respondent rather than the enterprise as a fully observed organizational entity. This means that the findings have reflected informed perceptions of enterprise reality rather than direct system-level performance logs or fully objective operational records. Fourth, the case-study-based nature of the research has provided contextual depth, but it has also limited broad generalizability across all industries, countries, and institutional environments. Digital economies vary significantly in terms of infrastructure, regulatory conditions, organizational maturity, and technology adoption culture, and those broader contextual differences have not been exhaustively represented in the study. Fifth, although the study has included readiness as a moderating variable and has added maturity and sensitivity analyses, the model has still simplified a highly complex enterprise reality into a manageable number of constructs. Important related factors such as organizational culture, leadership style, trust in AI, cybersecurity concerns, ethical governance, and sector-specific regulatory pressures have not been examined directly in the tested model. Sixth, the dependent variable of intelligent business process automation has been treated as a broad integrated construct, which has been analytically useful but may have compressed multiple dimensions of enterprise automation that could have been studied separately in greater detail. Seventh, the study has used SPSS-based statistical analysis and has therefore remained focused on linear relationships and standard inferential testing, which may not have captured more complex nonlinear or nested interactions within enterprise systems. These limitations have not invalidated the study, because the findings have still been statistically robust and theoretically grounded, but they have defined the boundaries within which the results should be interpreted. Accordingly, the study should be viewed as a strong empirical contribution to understanding AI-driven enterprise decision support and intelligent business process automation, while still leaving room for broader, deeper, and more methodologically diverse future investigation.

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