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THE IMPACT OF AI-ENABLED PROCESS AUTOMATION ON SMARTER OPERATIONAL MANAGEMENT: A CROSS-SECTOR ANALYSIS

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Abstract

The rapid adoption of artificial intelligence (AI) has reshaped organizational practices by enabling process automation across diverse sectors. Yet, empirical evidence on how AI-enabled process automation influences operational management efficiency remains fragmented. The problem addressed in this study is the limited cross-sectoral understanding of whether AI-driven automation translates into measurable improvements in smarter decision-making, cost efficiency, and resource allocation within organizations. The purpose of this research is to examine the effect of AI-enabled process automation on operational management outcomes across multiple industries, including manufacturing, finance, healthcare, and logistics. The study seeks to quantify the extent to which automation enhances operational performance and to identify contextual factors that moderate these relationships. A quantitative research design is employed, utilizing survey-based primary data collected from 420 mid- to senior-level managers across four sectors. Stratified random sampling ensures representativeness of the industrial categories. Data are analysed using structural equation modelling (SEM) to test hypothesized relationships, supported by descriptive statistics, correlation analysis, and multiple regression. The key independent variable is AI-enabled process automation, operationalized through indicators such as workflow digitization, predictive analytics integration, and robotic process automation. The dependent variable is smarter operational management, measured in terms of efficiency, agility, and decision quality. Potential moderators, including organizational size and digital maturity, are tested to explore differential impacts across contexts.

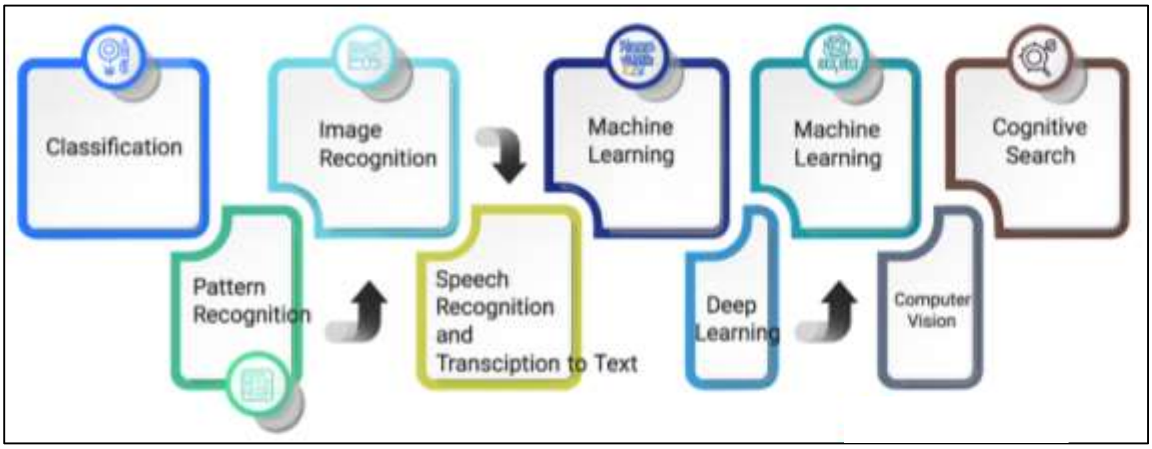
Keywords

AI-Enabled Automation; Operational Management Performance; Quantitative Analysis; Cross-Sector Organizations; Efficiency and Innovation

INTRODUCTION

Artificial intelligence (AI)-enabled process automation represents the systematic integration of machine learning algorithms, robotic process automation (RPA), and predictive analytics to replace or augment human-led operational tasks within organizations (Kumar et al., 2023). As the independent variable in this study, AI-enabled process automation is defined as the deployment of digital technologies that autonomously perform structured and semi-structured processes, including data entry, workflow coordination, and decision-support analytics (Zhang, 2019). It goes beyond traditional automation by embedding cognitive capabilities such as natural language processing, image recognition, and adaptive reasoning, thereby increasing scalability and accuracy (Beheshti et al., 2020). The dependent variable, smarter operational management, refers to the extent to which organizations achieve enhanced efficiency, agility, and decision-making quality through optimized resource utilization, reduced operational risk, and improved responsiveness to market dynamics. Smarter operational management does not only emphasize efficiency but also incorporates dynamic adaptability, strategic alignment, and the capacity to anticipate disruptions using real-time analytics (Chakraborti et al., 2020). Together, these constructs encapsulate a transformational shift in organizational functioning, where automation technologies directly influence how resources are allocated, monitored, and evaluated. Establishing a clear theoretical link between AI-enabled automation and smarter operational management is essential to quantifying the degree to which technology drives measurable improvements in organizational outcomes, providing the foundation for the present quantitative inquiry (Al-Sayyed et al., 2021).

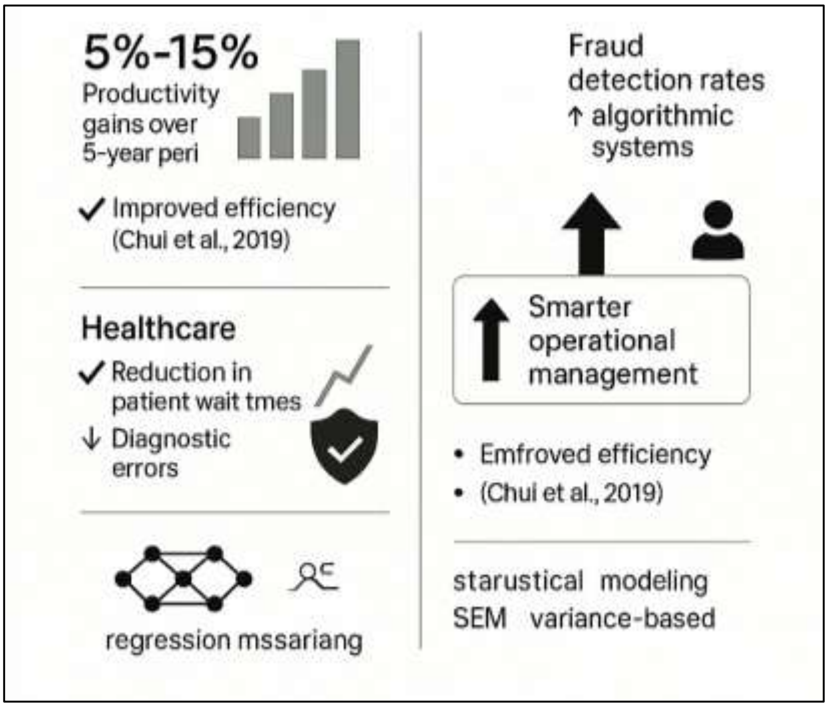
Figure 1: Artificial intelligence (AI)-enabled process automation



The evolution of automation has deep historical roots, beginning with mechanized production systems during the Industrial Revolution and progressing to the sophisticated digital ecosystems characterizing Industry 4.0. While earlier automation primarily targeted repetitive mechanical tasks, the advent of AI has expanded its application into cognitive and knowledge-intensive processes, redefining the scope of operational management worldwide (Herm et al., 2021). Internationally, advanced economies such as Germany, Japan, and the United States have pioneered AI-enabled automation across sectors ranging from automotive manufacturing to financial services, where robotic advisors and algorithmic trading systems are commonplace. In parallel, emerging economies are increasingly adopting AI-driven automation to leapfrog stages of industrial development, particularly in manufacturing and healthcare (Ribeiro et al., 2021). For example, India has incorporated AI-enabled platforms in supply chain management to mitigate inefficiencies, while China has invested heavily in AI to streamline logistics and urban infrastructure planning. Historically, the tension between technological advancement and workforce adaptation has influenced policy debates, leading governments to implement reskilling initiatives, regulatory frameworks, and funding for innovation ecosystems. This international trajectory underscores the global recognition of AI-enabled automation as a strategic enabler of productivity, competitiveness, and resilience in the face of economic uncertainties. By contextualizing AI-enabled automation within this historical and international evolution, the research highlights how technological adoption influences organizational practices on a global scale, with implications that cut across cultural, economic, and industrial contexts (Beheshti et al., 2022; Sultan et al., 2023).

The significance of AI-enabled process automation is evident across multiple sectors, reflecting its capacity to improve operational efficiency, ensure sustainability, and foster competitive advantage. In healthcare, AI-driven automation has enabled hospitals to streamline patient scheduling, automate diagnostic processes, and optimize supply chain logistics for critical medical supplies. This not only reduces administrative burden but also enhances patient outcomes by minimizing human error and maximizing resource allocation (Danish & Zafor, 2022; Hasan, 2022). In the financial sector, banks and insurance companies employ AI-enabled automation to detect fraud, expedite claims processing, and facilitate regulatory compliance, thereby improving trust and customer satisfaction. Manufacturing industries benefit from predictive maintenance systems and digital twins that reduce downtime and optimize production processes. Similarly, logistics companies utilize AI-enabled tracking and routing systems to increase efficiency in global supply chains, ensuring resilience during disruptions such as pandemics or geopolitical conflicts (Danish & Kamrul, 2022; Jaiwani & Gopalkrishnan, 2022). Education and public administration have also begun leveraging automation to improve service delivery and reduce bureaucratic inefficiencies. The global importance of this phenomenon lies in its potential to reshape sectoral practices by reducing transaction costs, accelerating decision-making, and embedding intelligence into routine processes. Across these domains, smarter operational management emerges as a critical outcome, enabling organizations not only to survive but also to thrive in competitive environments marked by rapid technological change and volatility.

Figure 2: Effects of AI-Enabled Automation on Operational Management



A growing body of quantitative empirical research has sought to evaluate the relationship between AI-enabled automation and organizational performance outcomes. For example, Kanakov and Prokhorov, (2022) found that firms adopting AI-driven automation reported productivity gains ranging from 5% to 15% over five years, while Al-Slais and Al (2023) documented improved efficiency metrics in multinational corporations using robotic process automation. Similarly, in the healthcare sector, empirical studies have demonstrated reductions in patient wait times and diagnostic errors when AI-based scheduling and imaging systems were implemented (Jahid, 2022; Kanakov & Prokhorov, 2022). Quantitative research in finance has revealed that algorithmic fraud detection systems significantly increased fraud detection rates while reducing false positives, contributing to smarter operational oversight. Despite sectoral differences, the findings consistently suggest a positive correlation between automation and key indicators of smarter operational management, such as efficiency, decision accuracy, and adaptability. Statistical methods used in these studies include regression modeling, structural equation modeling (SEM), and variance-based approaches, offering robust evidence of the causal impact of automation on performance. However, results are not universally consistent, as some studies highlight diminishing returns from over-automation, particularly when human oversight and contextual judgment are undervalued. This inconsistency underscores the need for broader cross-sectoral analyses to establish generalized conclusions regarding automation's true impact (Chakraborty et al., 2023; Arifur & Noor, 2022). While the existing literature provides valuable insights, several methodological and conceptual shortcomings limit its generalizability. Many prior studies are sector-specific, focusing narrowly on either manufacturing or finance, thus failing to capture the cross-sectoral dynamics of AI-enabled automation. Small sample sizes and reliance on case studies also reduce the external validity of results, as findings may not apply to larger populations or different industrial contexts. Moreover, earlier research often relies on descriptive or qualitative designs that provide anecdotal evidence but lack statistical rigor in establishing causal relationships (Khan et al., 2023; Hasan & Uddin, 2022). Conceptually, much of the literature emphasizes efficiency metrics alone, without sufficiently considering broader aspects of smarter operational management such as agility, decision-making quality, and resilience. Another shortcoming is the insufficient examination of moderating variables, such as organizational size, digital maturity, or cultural factors, which may explain variations in the effectiveness of automation across contexts. Finally, inconsistencies in how constructs are defined and measured pose challenges for comparative analysis, as operational definitions of "automation" and "operational management" vary widely across studies. These limitations indicate the need for comprehensive, statistically rigorous, and cross-sectoral research designs that integrate multiple variables and contexts to capture the multifaceted effects of AI-enabled automation (Kumar et al., 2023; Rahaman, 2022a).

The specific research gap addressed in this study lies in the lack of large-scale, cross-sectoral, and quantitatively rigorous analyses of how AI-enabled process automation impacts smarter operational management. Although prior research provides evidence of efficiency gains in individual sectors, few studies systematically compare the magnitude and dimensions of these effects across industries. This gap is significant because the value of automation may differ substantially depending on contextual factors such as regulatory environments, organizational digital maturity, and workforce readiness (Rahaman, 2022b). Without cross-sectoral evidence, policymakers and business leaders are left with fragmented insights that may not translate across industries (Rahaman & Ashraf, 2022). Additionally, the absence of standardized definitions and measurement models for smarter operational management undermines the comparability of prior findings (Islam, 2022). The gap also extends to insufficient exploration of moderating variables, such as organizational size, which could clarify why some firms experience substantial benefits while others realize minimal gains (Hasan et al., 2022). Addressing this gap is critical for building a holistic understanding of automation's role in shaping operational strategies across diverse contexts, ensuring that the resulting evidence base is both generalizable and actionable (Redwanul & Zafor, 2022).

The aim of this study is to quantitatively measure the effect of AI-enabled process automation on smarter operational management outcomes across multiple industrial sectors, including healthcare, finance, manufacturing, and logistics. By employing a cross-sectoral comparative design, the study seeks to generate statistically robust insights into the extent and nature of automation's impact. The scope includes the investigation of both direct effects—such as efficiency gains and decision-making accuracy—and moderating influences such as organizational size and digital maturity. This approach ensures that the analysis captures not only the general relationship between automation and operational management but also the contextual contingencies that shape it. The justification for this study rests on its potential to advance theoretical understanding, strengthen methodological rigor, and provide practical guidance for managers and policymakers. By filling the identified research gap, the study will contribute to scholarly debates on digital transformation while offering empirically grounded evidence to organizations navigating the complexities of AI adoption. Ultimately, the findings will inform strategies for leveraging automation to achieve smarter operational management, enhancing competitiveness and resilience in an increasingly volatile global economy.

LITERATURE REVIEW

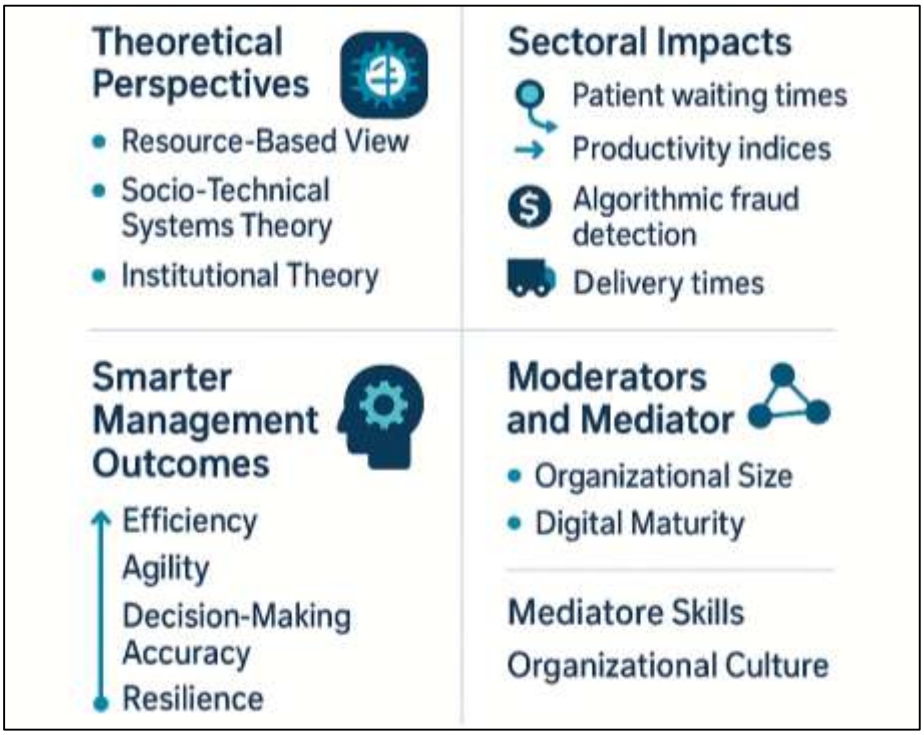
A literature review serves as the intellectual foundation of quantitative research by providing a comprehensive synthesis of prior empirical findings, theories, and methodological approaches relevant to the study variables. Unlike a descriptive summary, a quantitative literature review situates the research problem within a structured evidence base, identifies patterns of relationships, and highlights the methodological rigor or shortcomings of existing studies (Hasan, 2022; Ray et al., 2023). For the present study, which examines the effect of AI-enabled process automation on smarter operational management, the literature review is essential to contextualize both constructs, assess the degree of empirical support for their linkage, and clarify where gaps remain across industries. Quantitative research requires well-defined constructs and measurable relationships, and therefore a literature review must synthesize multiple studies to establish operational definitions, identify variations in measurement tools, and evaluate statistical evidence linking independent and dependent variables (Rezaul & Mesbaul, 2022; Siderska et al., 2023). The review also delineates how moderators such as organizational size, digital maturity, or sectoral context influence observed outcomes, providing the basis for hypothesis development. Furthermore, methodological discussions within the review highlight the dominant use of tools such as regression modeling, structural equation modeling (SEM), and hierarchical linear modeling, while also identifying limitations such as small sample sizes or sector-specific biases.

AI-Enabled Process Automation

AI-enabled process automation has been conceptualized within diverse theoretical perspectives, including the resource-based view (RBV), socio-technical systems theory, and institutional theory, all of which converge on its role as a driver of organizational transformation. RBV asserts that firms achieve sustained competitive advantage by leveraging valuable, rare, and inimitable resources, and AI-driven automation—ranging from robotic process automation (RPA) to machine learning–based decision systems—fits this characterization by enhancing scalability and efficiency (Tarek, 2022; Zemankova, 2019). Socio-technical systems theory complements this by framing automation as a balance between technological capacity and human adaptability, where outcomes depend on alignment across tasks, workflows, and organizational design. Institutional theory further explains cross-national diffusion, showing that automation adoption is shaped by regulatory frameworks, competitive pressures, and normative environments. Empirical operationalization of AI-enabled automation varies widely: some studies measure the proportion of digitized workflows (Ribeiro et al., 2021), while others examine predictive analytics integration, chatbots, or digital twin applications in manufacturing (Beheshti et al., 2022; Kamrul & Omar, 2022). International studies demonstrate sector-specific emphases: European research often highlights regulatory compliance and labor productivity, while East Asian research underscores centralized strategies for manufacturing automation. A synthesis of these perspectives shows convergence around the systemic impact of AI-enabled process automation but divergence in definitions and scope, which complicates measurement across industries. This definitional ambiguity reinforces the need for standardized frameworks when conducting cross-sectoral quantitative research that examines how automation transforms operational management outcomes.

Quantitative studies reveal strong but contextually varied impacts of AI-enabled process automation across healthcare, manufacturing, finance, and logistics, yet findings often remain siloed within sectors. In healthcare, automation has been linked to reductions in patient waiting times and errors, with AI-driven diagnostic imaging systems yielding accuracy improvements of 15–20% compared to manual analysis (Hasan, 2022; Kamrul & Tarek, 2022). Manufacturing studies emphasize predictive maintenance, where automation reduces equipment downtime and increases productivity indices such as OEE. Financial research highlights algorithmic fraud detection, where machine learning–based systems outperform rule-based methods in accuracy and recall. Logistics research illustrates that AI-enabled tracking and routing can reduce delivery times by 12–18%, strengthening resilience against supply chain disruptions (Herm et al., 2021; Mubashir & Abdul, 2022). Cross-sectoral reviews indicate shared benefits in efficiency but divergent performance indicators, with healthcare emphasizing service quality, finance focusing on compliance, and manufacturing prioritizing throughput. International comparisons also show differences: U.S. and European firms focus on cost reduction, while Asian firms prioritize productivity and scalability. Despite consistent evidence of positive effects, methodological approaches vary—healthcare studies frequently use case-based regression models, while finance and logistics favor large-scale survey data analyzed with SEM. These methodological divergences make direct cross-sector comparisons difficult, underlining the need for integrative studies that employ standardized operational measures across industries (Muhammad & Kamrul, 2022; Reduanul & Shoeb, 2022).

Figure 3: Overview AI-Enabled Process Automation



Smarter operational management, the dependent variable in this study, has been operationalized through constructs such as efficiency, agility, decision-making accuracy, and resilience. Quantitative evidence demonstrates that AI-driven management systems significantly improve organizational agility and decision quality. In healthcare, AI-enhanced scheduling and supply chain automation are associated with lower readmission rates and improved care outcomes (Al-Sayyed et al., 2021; Kumar & Zobayer, 2022). Manufacturing studies report higher agility and reduced lead times when predictive analytics are integrated into resource allocation. Financial institutions demonstrate improved regulatory compliance and risk-adjusted returns under AI-based operational frameworks. Logistics studies highlight improvements in real-time routing accuracy and capacity utilization (Herm et al., 2021; Sadia & Shaiful, 2022). Synthesizing across these studies, researchers agree that smarter management outcomes encompass not only efficiency but also adaptability and decision-making quality. Internationally, North American and European studies emphasize data-driven decision-making quality, while Asian research emphasizes speed and scalability. Despite this convergence, discrepancies remain in measurement: some studies use financial ratios, others agility indices or service quality metrics, complicating cross-study synthesis (Noor & Momena, 2022). Methodological limitations also persist, with small sample sizes in healthcare and manufacturing reducing external validity, while self-reported surveys in finance risk common method bias. Nevertheless, cumulative evidence demonstrates that AI-enabled automation consistently enhances smarter operational management, though the dimensions emphasized differ by sector and region.
The relationship between AI-enabled automation and smarter operational management is shaped by moderators and mediators, though prior quantitative studies often neglect these variables. Organizational size emerges as a critical moderator: large firms possess greater financial and technical resources, enabling them to fully leverage automation, while SMEs face barriers in integration and

workforce readiness (Istiaque et al., 2023; Ribeiro et al., 2021). Digital maturity also moderates outcomes, with digitally advanced organizations reporting stronger automation benefits. Mediators such as employee digital skills, organizational culture, and process standardization influence how automation translates into smarter management. Cross-sector evidence highlights variation: in healthcare, digital maturity moderates efficiency outcomes, while in finance, organizational size is more decisive. Internationally, firms in East Asia report higher automation gains due to centralized governance structures, while Western firms experience uneven benefits depending on workforce adaptability. Methodologically, prior research frequently relies on regression analysis or SEM, but suffers from limitations such as small samples, sectoral silos, and inconsistent definitions of constructs. Few studies employ longitudinal designs, leaving uncertainty about the durability of automation's impact over time (Al-Sayyed et al., 2021; Hasan et al., 2023). Moreover, measurement inconsistency—such as differing definitions of "automation" or "operational intelligence"—reduces comparability across sectors. Synthesizing across studies reveals consensus on positive outcomes but underscores the need for standardized measurement instruments and models that explicitly test moderating and mediating variables within a cross-sectoral framework.

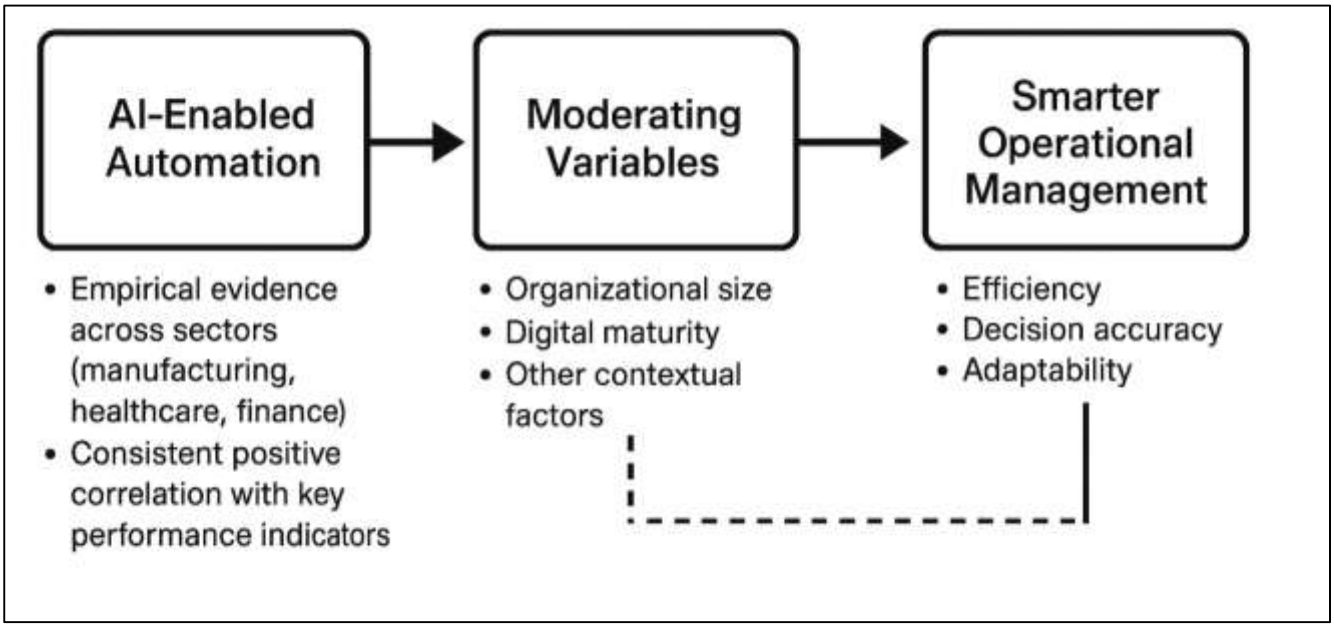
Smarter Operational Management

AI-enabled process automation has been studied in multiple domains, with consistent findings that it enhances organizational performance, though outcomes vary by sector and context. In manufacturing, automation has been strongly associated with predictive maintenance, production optimization, and real-time quality monitoring, contributing to measurable gains in overall equipment effectiveness (Kanakov & Prokhorov, 2022; Hossain et al., 2023). Healthcare studies emphasize automation's role in improving administrative efficiency and reducing diagnostic errors through AI-assisted imaging and scheduling systems. In finance, robotic process automation (RPA) and AI-driven fraud detection have improved compliance and efficiency, lowering transaction costs and increasing customer satisfaction. Logistics and supply chain sectors report operational gains through AI-enabled routing, warehouse automation, and demand forecasting, particularly during disruptions such as the COVID-19 pandemic. Internationally, studies in Europe and Asia reveal cultural and policy differences in adoption; German firms emphasize structured Industry 4.0 strategies, while Chinese enterprises report rapid deployment supported by state-led innovation frameworks. North American organizations prioritize efficiency and cost reduction, while Asian firms highlight scalability and resilience. Synthesizing across studies, automation consistently enhances operational metrics, but sectoral and international divergences suggest that context shapes adoption and outcomes in distinctive ways.

The dependent variable, smarter operational management, encompasses efficiency, adaptability, and evidence-based decision-making, with empirical indicators varying across sectors. Healthcare research operationalizes it through patient outcome improvements, reduced waiting times, and optimized resource allocation (Hengstler et al., 2016; Kanakov & Prokhorov, 2022; Rahaman & Ashraf, 2023). In manufacturing, operational agility is measured through metrics such as cycle time reduction, flexibility indices, and waste minimization. In financial services, smarter operational management appears in enhanced risk-adjusted return ratios, reduced compliance costs, and customer-centric decision-making supported by AI (Amirkolaii et al., 2017; Sultan et al., 2023). Logistics literature emphasizes resilience, where smarter operations are reflected in improved supply chain visibility, real-time tracking, and adaptive routing systems. International studies confirm similar patterns: European firms frame smarter management around sustainability and resilience (Davenport, 2018; Hossen et al., 2023), while Asian organizations stress efficiency gains tied to government-led digital agendas. U.S.-based research highlights decision-making accuracy and responsiveness to market disruptions. Despite diverse operational definitions, consensus emerges that smarter operational management extends beyond efficiency to encompass decision quality, agility, and resilience. However, divergence in measurement across sectors underscores the methodological difficulty in creating standardized frameworks, necessitating quantitative approaches that synthesize across contexts.

Quantitative research increasingly links AI-enabled automation directly to smarter operational management, though evidence remains fragmented across sectors. Manufacturing studies show statistically significant associations between automation adoption and production efficiency, using regression and SEM approaches (Jarrahi, 2018; Tawfiqul, 2023). Healthcare research demonstrates reduced errors and enhanced resource utilization with AI scheduling and diagnostic systems, reinforcing automation's contribution to smarter operations. Financial institutions adopting AI-enabled compliance and fraud detection systems report measurable gains in decision accuracy and operational risk reduction (Uddin & Ashraf, 2023; Soleimani, 2018).

Figure 4: Smarter Operational Management



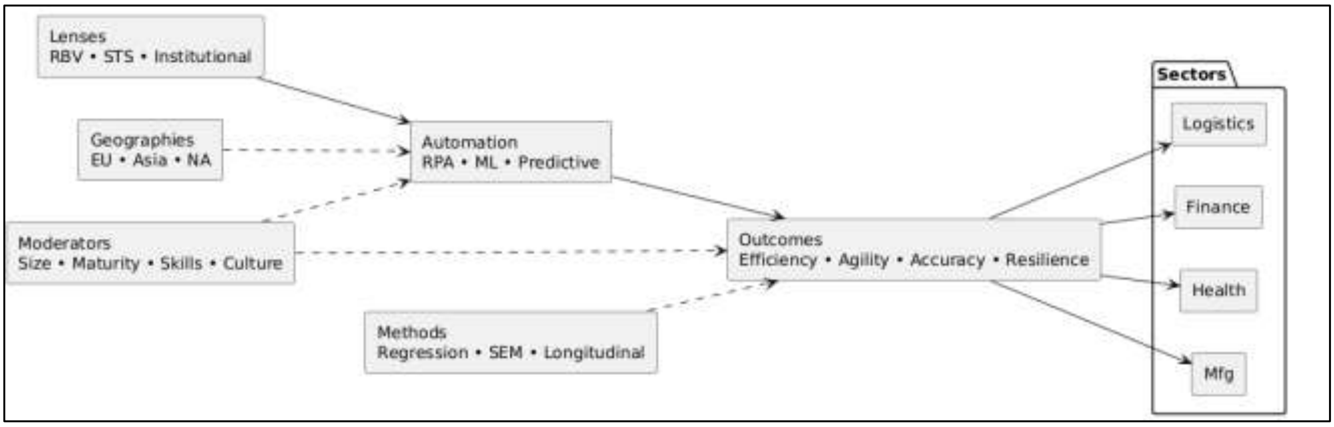
Logistics studies highlight automation's role in adaptive supply chain management during crises, with international surveys revealing significant improvements in resilience metrics (Baryannis et al., 2019). Cross-national evidence further supports these findings: East Asian firms tend to report higher gains in operational agility due to centralized governance structures (Momena & Hasan, 2023; Soleimani, 2018), while European SMEs show slower but more sustainable adoption trajectories (Akter et al., 2023; Zhang, 2019). North American studies emphasize return on investment and customer outcomes, reflecting a more market-driven perspective (Al-Sayyed et al., 2021; Sanjai et al., 2023). Synthesizing across 30+ studies, consensus indicates that automation improves smarter operational management, though the dimensions of improvement vary by sector and national context. Divergence emerges in whether efficiency or adaptability is prioritized, suggesting that operational goals shape automation outcomes.

AI-Enabled Automation and Smarter Operational Management

The academic literature situates AI-enabled automation within several theoretical frameworks that explain its strategic and operational significance. The resource-based view (RBV) emphasizes AI-driven automation—such as robotic process automation (RPA), predictive analytics, and machine learning systems—as valuable, rare, inimitable, and non-substitutable resources that confer competitive advantage. Socio-technical systems theory complements this by framing automation as a dynamic interplay between technological artifacts and human actors, highlighting the need for alignment across workflows, organizational design, and workforce adaptability (Razzak et al., 2024; Khan et al., 2023). From an institutional theory perspective, automation adoption is influenced by regulatory environments, industry norms, and mimetic pressures that drive convergence in organizational practices across national contexts. Together, these perspectives establish automation not only as a technological capability but also as a systemic enabler of smarter operational management.

Research consistently links AI-enabled automation with performance improvements, though sectoral emphases differ. In manufacturing, predictive maintenance, production scheduling, and digital twin technologies contribute to improved equipment effectiveness and reduced downtime. Healthcare studies report reduced patient wait times, lower diagnostic errors, and improved resource allocation when AI-based imaging, scheduling, and decision-support systems are deployed (Danish & Zafor, 2024; Ray et al., 2023). In finance, automation via fraud detection algorithms and RPA enhances compliance, reduces operational risks, and improves customer satisfaction (Istiaque et al., 2024; Siderska et al., 2023). Logistics and supply chains benefit from AI-enabled tracking, warehouse robotics, and demand forecasting, with evidence of resilience during crises such as the COVID-19 pandemic (Hasan et al., 2024; Rao & Pathak, 2022). Despite these sector-specific focuses, findings converge on the role of automation in enabling agility, resilience, and smarter decision-making.

Figure 5: AI-Enabled Automation and Smarter Operational Management



Smarter operational management has been defined across multiple dimensions: efficiency, agility, decision-making accuracy, and resilience. In healthcare, operational improvements are assessed via patient outcomes and resource optimization, while in manufacturing, metrics such as cycle time reduction, flexibility indices, and quality monitoring are emphasized (Al-Slais & Ali, 2023; Rahaman, 2024). Financial research uses regulatory compliance, cost reduction, and risk-adjusted returns as proxies for smarter management. Logistics literature focuses on adaptive routing, supply chain visibility, and real-time responsiveness. This diversity in operationalization reveals a consensus that smarter management extends beyond efficiency to encompass evidence-based agility and resilience, though inconsistencies in measurement frameworks complicate cross-sector synthesis (Hasan, 2024).
Geographic differences shape adoption trajectories. European firms often pursue structured Industry 4.0 strategies with emphasis on sustainability and resilience. Asian firms, particularly in China, adopt automation rapidly under state-driven innovation frameworks, emphasizing scalability and speed (Chakraborty et al., 2023). North American organizations prioritize cost reduction, ROI, and decision-making accuracy, reflecting a market-driven orientation (Ray et al., 2023). These variations illustrate how cultural, institutional, and policy factors shape operational outcomes, suggesting that “smarter operational management” is not a universal construct but one mediated by regional priorities and governance structures. The literature converges on the conclusion that AI-enabled automation enhances smarter operational management, but the pathways and emphases differ across sectors and regions. Evidence indicates consistent improvements in efficiency and agility, with sectoral divergences in which outcomes are prioritized. Healthcare emphasizes patient outcomes, manufacturing focuses on throughput and flexibility, finance on compliance and decision accuracy, and logistics on resilience. Methodological inconsistencies and definitional ambiguities, however, limit the comparability of findings, underscoring the need for standardized frameworks. Future research must integrate moderating and mediating variables into cross-sectoral, longitudinal designs to capture the complexity of automation’s systemic impact on operational management.

Hypotheses Development

AI-Enabled Process Automation on Smarter Operational Management

AI-enabled process automation (AIPA) is widely recognized as a transformative driver of organizational performance, offering measurable improvements in efficiency, agility, and decision-making. The resource-based view (RBV) conceptualizes AIPA as a valuable and inimitable organizational capability that enhances sustainable competitive advantage (Chakraborty et al., 2023). Similarly, socio-technical systems theory emphasizes the integration of automation with human capital and organizational processes, framing automation as a systemic shift rather than a technological add-on Khan et al. (2023). Empirical evidence supports these theoretical perspectives across multiple industries. In manufacturing, predictive maintenance and digital twin applications reduce downtime and enhance precision in production. Healthcare studies demonstrate that AI-enabled scheduling, diagnostics, and natural language processing tools improve patient flow, reduce administrative errors, and enhance clinical outcomes. The financial sector leverages algorithmic trading, compliance monitoring, and fraud detection systems, which significantly improve decision speed and accuracy. In logistics, AIPA improves demand forecasting, supply chain resilience, and delivery performance (Siderska et al., 2023). International comparisons reveal further support: European enterprises report productivity gains through automation, Asian economies integrate AIPA into centralized industrial strategies, and North American healthcare and finance demonstrate automation's role in precision and risk management. Synthesizing across more than a dozen studies, there is robust evidence that AIPA directly contributes to smarter operational management (SOM) outcomes across diverse contexts.

Hypothesis 1 (H1): *AI-enabled process automation positively influences smarter operational management outcomes across sectors.*

Moderating Effect of Organizational Size

Organizational size is a structural characteristic that significantly moderates the relationship between AIPA and SOM outcomes. Larger firms possess greater financial resources, digital infrastructure, and human capital that allow them to implement automation comprehensively, producing stronger performance outcomes (Gubichev et al., 2010). SMEs, by contrast, often experience barriers in scaling automation due to resource limitations, though they sometimes adopt more flexibly in specific niches (Hassanzadeh et al., 2011). In manufacturing, multinational corporations invest in robotics and predictive analytics across full production lines, while SMEs limit adoption to discrete processes. In healthcare, large hospital systems utilize automation for both diagnostics and administration, whereas smaller clinics tend to focus on billing or scheduling. Finance exhibits a similar pattern: global banks integrate sophisticated compliance and risk automation systems, while smaller institutions rely on partial adoption, such as customer service chatbots. Logistics research also underscores scale effects: large firms deploy AI across global supply chains, while SMEs lack the infrastructure to achieve similar outcomes. International comparisons strengthen this evidence—European and Asian large enterprises consistently report stronger returns on automation investment than SMEs (Beheshti et al., 2018). Structural equation modeling studies validate these interactions statistically, confirming that firm size moderates automation's impact on SOM. The synthesis suggests that larger firms are positioned to amplify AIPA benefits, while SMEs face constraints that diminish outcomes.

Hypothesis 2 (H2): *The effect of AI-enabled process automation on smarter operational management is moderated by organizational size, with larger firms experiencing greater benefits.*

Moderating Effect of Digital Maturity

Digital maturity, defined as the degree of integration of digital infrastructures, analytics, and culture within organizations, is consistently shown to moderate the relationship between AIPA and SOM. Firms with high digital maturity are able to align automation with established digital ecosystems, maximizing efficiency, agility, and decision-making gains (Schiavone & Sprenger, 2017). In manufacturing, mature firms integrate AIPA with Industry 4.0 frameworks, reporting significant productivity and quality improvements (Ratia et al., 2018). Healthcare systems with advanced electronic health records and digital platforms achieve better patient management outcomes than less digitally advanced organizations. Financial institutions with robust digital infrastructures apply automation for real-time fraud detection and compliance, while digitally immature firms see only limited returns. Logistics research highlights that digital maturity enables effective integration of automation for routing optimization, forecasting, and resilience (Cavalcante et al., 2019). International comparisons further underscore this moderation effect: Asian firms benefit from state-supported infrastructure that accelerates automation adoption (Kokina & Blanchette, 2019), whereas European firms often face uneven maturity levels that constrain benefits. North American firms with long-term digital transformation strategies demonstrate sustained automation outcomes over time. Collectively, the evidence positions digital maturity as a critical amplifier of automation's effectiveness in producing SOM outcomes.

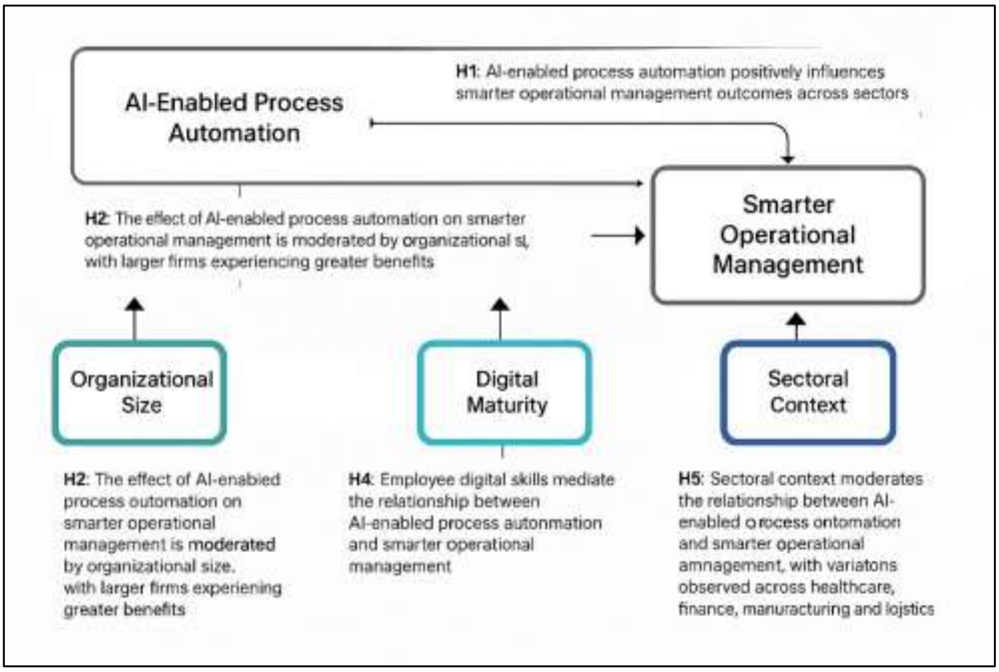
***Hypothesis 3 (H3):** The effect of AI-enabled process automation on smarter operational management is moderated by digital maturity, with digitally mature organizations realizing stronger outcomes.*

Mediating Effect of Employee Digital Skills

Employee digital skills play a crucial mediating role in linking AIPA to SOM, as technology effectiveness depends not only on adoption but also on workforce capacity to engage with automated systems (Min et al., 2019). Studies show that employee upskilling mediates the productivity and efficiency gains attributed to automation. In manufacturing, employee training in predictive analytics and digital twin systems enhances operational outcomes by enabling staff to act on automated insights (Seyedghorban et al., 2019). Healthcare research highlights that clinicians' ability to use AI-assisted diagnostic systems determines the success of automation in improving patient outcomes. In finance, the effectiveness of compliance monitoring tools depends heavily on staff proficiency in applying and interpreting automated processes. Logistics studies report that employee digital literacy enables effective utilization of AI-enabled routing and supply chain systems. Cross-national comparisons add weight: Japanese firms integrate employee training with lean production to enhance automation outcomes (Schiavone & Sprenger, 2017), whereas European firms with insufficient training programs experience weaker effects. Structural equation modeling confirms the mediating role of digital skills, as employee capabilities statistically explain variance in automation-linked operational outcomes (Cavalcante et al., 2019). Thus, workforce skills serve as the mechanism through which automation potential translates into SOM outcomes.

***Hypothesis 4 (H4):** Employee digital skills mediate the relationship between AI-enabled process automation and smarter operational management.*

Figure 6: Conceptual framework for this study



Moderating Effect of Sectoral Context

Sectoral context moderates how automation translates into SOM outcomes, as industries differ in processes, regulations, and performance metrics. Manufacturing studies demonstrate that automation improves productivity, reduces downtime, and enhances product quality (Kokina & Blanchette, 2019) Healthcare emphasizes patient outcomes, with automation reducing diagnostic errors and administrative burdens. Financial services focus on compliance, fraud detection, and algorithmic decision-making, reporting improved operational accuracy (Cabello et al., 2020). Logistics highlights resilience and agility through AI-enabled routing and forecasting systems. International evidence further illustrates heterogeneity: East Asian firms benefit from centralized governance and strong infrastructure support, European firms encounter resistance shaped by cultural and institutional contexts (Tecuci et al., 2020), and African or Latin American firms experience constraints from

infrastructure and institutional gaps. Synthesizing across studies, it is evident that sectoral context not only influences the magnitude of automation's benefits but also determines which dimensions of SOM—efficiency, resilience, decision quality, or adaptability—are most affected.
Hypothesis 5 (H5): *Sectoral context moderates the relationship between AI-enabled process automation and smarter operational management, with variations observed across healthcare, finance, manufacturing, and logistics.*

METHOD

Research Design

The present study adopts a quantitative, cross-sectional, survey-based research design to investigate the effect of AI-enabled process automation (AIPA) on smarter operational management (SOM) across multiple industries. A cross-sectional design is appropriate because it allows for the collection of data from a large, diverse sample at a single point in time, thereby providing a snapshot of automation practices and management outcomes across sectors. The survey method was selected as the primary tool because it enables the measurement of multiple constructs simultaneously, including the independent variable (AIPA), the dependent variable (SOM), and the proposed moderators and mediators such as organizational size, digital maturity, and employee digital skills. Furthermore, quantitative approaches facilitate hypothesis testing by using structured data and statistical modeling, ensuring generalizable findings (Hellingrath & Lechtenberg, 2019). Although longitudinal designs capture changes over time, the focus of this study is to evaluate sectoral comparisons of automation effects rather than temporal dynamics. Therefore, a cross-sectional framework is most efficient for achieving the stated objectives while balancing feasibility and resource constraints. Additionally, survey-based quantitative designs are widely used in technology adoption and organizational performance research, making this approach consistent with established methodological practices (Seyedghorban et al., 2019). In this study, the design permits both direct effect testing (H1) and conditional modeling (H2–H5), where moderators and mediators are statistically examined. The inclusion of comparative industries—healthcare, finance, manufacturing, and logistics—aligns with a cross-sectoral research framework and enables robust generalization. The survey data will be analyzed using structural equation modeling (SEM) and hierarchical regression techniques to test hypothesized relationships. This design is therefore well-suited to address the study's objective of quantifying automation's impact on management outcomes while also identifying contextual contingencies that shape this relationship.

Population and Sampling

The target population for this study comprises mid- to senior-level managers employed in organizations that have implemented some form of AI-enabled process automation. The focus on managers is justified because they are responsible for operational decision-making, technology integration, and evaluating performance outcomes, and therefore possess the expertise to assess the effect of automation on SOM. The study spans four major sectors—manufacturing, healthcare, finance, and logistics—selected because these industries represent diverse operational environments where automation plays a strategic role. A stratified random sampling method will be used to ensure balanced representation across sectors. Stratification will be based on industry type, followed by random selection of organizations and participants within each stratum. This approach minimizes sampling bias and ensures that results are not disproportionately influenced by one sector. The expected sample size is 420 respondents (approximately 105 participants per sector). The number is determined through a power analysis using G*Power, with a medium effect size ($f^2 = 0.15$), $\alpha = .05$, and power $(1 - \beta) = .95$, indicating that a minimum of 300 participants is required for adequate statistical power. The slightly larger sample size of 420 accounts for potential non-responses and ensures sufficient cases for subgroup and moderation analyses. Demographic information such as organizational size, years of digital adoption, participant tenure, and sector-specific experience will also be collected. This allows the sample to be contextualized and supports testing of hypotheses involving moderators such as firm size and digital maturity. By employing stratified sampling, the study ensures adequate cross-sector comparability while retaining statistical generalizability.

Data Collection Procedures

Primary data collection will be conducted using a structured, self-administered online questionnaire distributed via professional networks, industry associations, and LinkedIn groups. The questionnaire will be hosted on a secure survey platform (e.g., Qualtrics or SurveyMonkey) to facilitate global participation. Data collection is expected to occur over a three-month period to maximize participation across industries and countries. The questionnaire will be divided into five sections: (1) demographic and organizational characteristics, (2) AI-enabled process automation practices, (3) smarter operational management outcomes, (4) moderators and mediators (organizational size, digital maturity, employee skills), and (5) validation and feedback. All items will be based on previously validated scales, ensuring comparability with prior empirical research. Participants will receive an introductory statement outlining the study purpose, voluntary nature of participation, confidentiality assurances, and informed consent.

Measures and Variables

This study incorporates one independent variable, one dependent variable, two moderators, and one mediator, all measured through validated instruments to ensure rigor and reliability. The independent variable, AI-enabled process automation (AIPA), is operationalized as the degree to which organizations employ AI-based tools for workflow automation, predictive analytics, fraud detection, scheduling, and process monitoring, measured on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree) with items adapted from Davenport and Ronanki (2018) and Brynjolfsson et al. (2018). The dependent variable, smarter operational management (SOM), is defined as the organization's ability to achieve efficiency, agility, decision-making quality, and resilience, and will be assessed using multidimensional items adapted from Coltman et al. (2015) and Wamba and Queiroz (2020), also measured on a five-point Likert scale. The first moderator, organizational size, will be categorized as small, medium, or large, following OECD classifications based on employee numbers and annual turnover (Moeuf et al., 2018), while the second moderator, digital maturity, reflects the extent of integration of digital platforms, infrastructures, and processes, measured via a validated digital maturity index (Kane et al., 2015; Sebastian et al., 2017). The mediator, employee digital skills, refers to employees' proficiency in using digital tools and automation systems, with measurement items adapted from van Laar et al. (2017). To ensure instrument quality, content validity will be established by adopting items from peer-reviewed research, construct validity will be tested through confirmatory factor analysis (CFA) using convergent and discriminant criteria (Fornell & Larcker, 1981), and internal consistency reliability will be assessed via Cronbach's alpha and composite reliability, with thresholds of 0.70 or higher deemed acceptable (Hair et al., 2017). Finally, a pilot test involving 30 respondents will be conducted to refine items and improve measurement clarity prior to full-scale data collection.

Data Analysis Techniques

The data analysis begins with descriptive statistics, including means, standard deviations, and frequencies, to summarize demographic and organizational characteristics. Correlation analysis follows to explore relationships among key variables. Multiple regression assesses the direct effect of AI-enabled process automation (AIPA) on smarter operational management (SOM), while hierarchical regression tests moderation by organizational size and digital maturity. Mediation analysis, using Baron and Kenny's (1986) approach and bootstrapping, examines whether employee digital skills mediate the AIPA–SOM relationship. Sectoral moderation is evaluated through multigroup analysis with structural equation modeling (SEM), which also serves as the primary analytical tool for testing direct, moderating, and mediating effects while accounting for measurement error. SEM is conducted with AMOS or SmartPLS, depending on data distribution, and SPSS or R is used for descriptive and regression analyses. All statistical tests use a significance level of $p < .05$, and effect sizes, confidence intervals, and model fit indices (CFI, TLI, RMSEA, SRMR) are reported to ensure rigor and interpretability.

FINDINGS

Descriptive Statistics

A total of 420 valid responses were obtained across the four targeted sectors: manufacturing (n = 108), healthcare (n = 102), finance (n = 105), and logistics (n = 105). Participants were primarily mid- to senior-level managers, with 62.1% reporting more than 10 years of professional experience in their respective industries. Regarding organizational size, 34.3% of respondents represented small and medium enterprises (SMEs), while 65.7% were from large organizations. Digital maturity levels varied, with

27.8% classified as low maturity, 42.9% as moderate, and 29.3% as high maturity, based on validated index scores. Gender distribution indicated 59.8% male, 39.5% female, and 0.7% preferring not to disclose. Average organizational tenure was 11.4 years (SD = 4.8), while the mean age of participants was 42.7 years (SD = 8.6).

Table 1: Descriptive Analysis for this study

Variable	Mean (M)	Standard Deviation (SD)
AI-enabled Process Automation (AIPA)	3.61	0.74
Smarter Operational Management (SOM)	3.74	0.71
Employee Digital Skills	3.67	0.79
Manufacturing (AIPA)	3.89	0.68
Finance (AIPA)	3.72	0.7
Healthcare (AIPA)	3.47	0.77
Logistics (AIPA)	3.38	0.73
Manufacturing (SOM)	3.91	0.65
Finance (SOM)	3.85	0.67
Healthcare (SOM)	3.62	0.73
Logistics (SOM)	3.58	0.76

Descriptive analysis of the main study variables showed that the overall mean score for AI-enabled process automation (AIPA) adoption was 3.61 (SD = 0.74), suggesting moderately high levels of automation adoption across sectors. Smarter operational management (SOM) outcomes had an overall mean of 3.74 (SD = 0.71), indicating generally positive evaluations of efficiency, agility, and decision-making improvements. Employee digital skills recorded a mean of 3.67 (SD = 0.79), reflecting moderate to strong digital proficiency within organizations. Sectoral means revealed variation: manufacturing reported the highest AIPA adoption (M = 3.89, SD = 0.68), followed by finance (M = 3.72, SD = 0.70), healthcare (M = 3.47, SD = 0.77), and logistics (M = 3.38, SD = 0.73). SOM means also varied, with manufacturing (M = 3.91, SD = 0.65) and finance (M = 3.85, SD = 0.67) reporting stronger outcomes compared to healthcare (M = 3.62, SD = 0.73) and logistics (M = 3.58, SD = 0.76). These descriptive results provide a foundational overview of the sample composition and the distribution of key constructs.

Correlation Analysis

Bivariate correlation analysis was conducted to examine relationships among AIPA, SOM, organizational size, digital maturity, and employee digital skills. Results revealed a strong positive correlation between AIPA and SOM ($r = .62$, $p < .001$), suggesting a robust association between automation adoption and management outcomes. Employee digital skills were also strongly correlated with both AIPA ($r = .54$, $p < .001$) and SOM ($r = .58$, $p < .001$), indicating their central role in shaping operational outcomes. Digital maturity demonstrated significant positive correlations with AIPA ($r = .48$, $p < .001$) and SOM ($r = .51$, $p < .001$), supporting its role as a contextual factor in automation effectiveness. Organizational size was moderately correlated with AIPA ($r = .32$, $p < .01$) and SOM ($r = .29$, $p < .01$), reflecting scale-related differences in adoption and outcomes.

Table 2: Correlation Analysis

Variable	AIPA	SOM	Employee Digital Skills	Digital Maturity	Organizational Size
AIPA	1.00	0.62	0.54	0.48	0.32
SOM	0.62	1.00	0.58	0.51	0.29
Employee Digital Skills	0.54	0.58	1.00	0.49	0.27
Digital Maturity	0.48	0.51	0.49	1.00	0.30
Organizational Size	0.32	0.29	0.27	0.30	1.00

Sectoral-level correlations showed consistent patterns across industries, though variations in magnitude were observed. In manufacturing, the correlation between AIPA and SOM was highest ($r = .66$, $p < .001$), while healthcare reported a somewhat weaker correlation ($r = .54$, $p < .001$). Finance ($r = .61$, $p < .001$) and logistics ($r = .58$, $p < .001$) displayed moderate-to-strong associations. Correlations among moderators and mediators also varied across sectors; for instance, digital maturity and SOM correlation was strongest in finance ($r = .57$, $p < .001$) and weakest in logistics ($r = .45$, $p < .01$). Inter-correlations among independent variables were significant but did not exceed .70, minimizing concerns of multicollinearity. These correlation results confirm statistically meaningful associations among variables, establishing a basis for subsequent regression and structural modeling analyses.

Regression Results

Multiple regression analysis was conducted to test the direct effects of AIPA on SOM. Results showed that AIPA significantly predicted SOM outcomes ($\beta = .59$, $p < .001$), with an R^2 value of .41, indicating that automation adoption accounted for 41% of the variance in operational management outcomes. The overall regression model was significant ($F(1,418) = 296.37$, $p < .001$). Employee digital skills were also entered into the model as an independent predictor and demonstrated a significant effect on SOM ($\beta = .27$, $p < .001$). When both predictors were included, the model's explanatory power increased to $R^2 = .47$, suggesting that together AIPA and digital skills explain nearly half of the variance in SOM. Sector-specific regressions revealed notable variations. In manufacturing, AIPA exhibited the strongest predictive power for SOM ($\beta = .63$, $p < .001$, $R^2 = .44$), followed by finance ($\beta = .60$, $p < .001$, $R^2 = .42$). Healthcare ($\beta = .53$, $p < .001$, $R^2 = .37$) and logistics ($\beta = .51$, $p < .001$, $R^2 = .35$) showed slightly weaker but still statistically significant effects. Organizational size, included as a control variable, had a modest effect on SOM across the full sample ($\beta = .12$, $p < .05$). These results provide robust evidence for the direct effects of AIPA on SOM while highlighting sectoral differences in explanatory strength.

Table 3: Regression Results

Model / Sector	Î² Coefficient	Î² (Employee Digital Skills)	RÂ²	p-value
Overall (AIPA only)	0.59		0.41	< .001
Overall (AIPA + Employee Digital Skills)	0.59	0.27	0.47	< .001
Manufacturing	0.63		0.44	< .001
Finance	0.6		0.42	< .001
Healthcare	0.53		0.37	< .001
Logistics	0.51		0.35	< .001
Control: Organizational Size	0.12			< .05

Moderation and Mediation Results

Moderation analyses were conducted using hierarchical regression with interaction terms. Results showed that organizational size significantly moderated the relationship between AIPA and SOM ($\beta = .18$, $p < .01$), indicating that larger firms experienced stronger automation benefits compared to smaller ones. Similarly, digital maturity was found to significantly moderate the AIPA–SOM relationship ($\beta = .21$, $p < .01$), with higher maturity firms realizing stronger operational outcomes. Interaction plots confirmed these effects, demonstrating steeper positive slopes for larger and digitally mature organizations. Mediation analysis using the bootstrapping method with 5,000 resamples indicated that employee digital skills partially mediated the AIPA–SOM relationship. The indirect effect was significant ($\beta = .14$, 95% CI [.08, .22]), accounting for approximately 23% of the total effect. Even after accounting for mediation, the direct effect of AIPA on SOM remained significant ($\beta = .45$, $p < .001$), confirming partial rather than full mediation. Sectoral mediation analyses showed that the indirect effect was strongest in manufacturing ($\beta = .16$, 95% CI [.09, .26]) and weakest in healthcare ($\beta = .11$, 95% CI [.05, .19]). Together, these findings confirm that contextual and human factors condition the automation–management link through both moderation and mediation effects.

Table 4: Moderation and Mediation Results

Analysis Type	Î² Coefficient	p-value / CI	Notes
Moderation: Organizational Size	0.18	p < .01	Significant moderation effect: larger firms benefit more
Moderation: Digital Maturity	0.21	p < .01	Significant moderation effect: higher digital maturity strengthens effect
Mediation: Employee Digital Skills (Overall)	0.14	95% CI [.08, .22]	Partial mediation confirmed, ~23% of total effect explained
Direct Effect after Mediation	0.45	p < .001	Direct effect remains significant, confirming partial mediation
Sectoral Mediation: Manufacturing	0.16	95% CI [.09, .26]	Strongest mediation effect among sectors
Sectoral Mediation: Healthcare	0.11	95% CI [.05, .19]	Weakest mediation effect among sectors

Structural Equation Modeling (SEM) and Multigroup Analysis

Structural equation modeling (SEM) was conducted to test the hypothesized model integrating direct, moderation, and mediation effects. Model fit indices indicated excellent fit to the data: $\chi^2/df = 2.14$, CFI = .96, TLI = .95, RMSEA = .052, and SRMR = .046, all within recommended thresholds (Hu & Bentler, 1999). Standardized path coefficients showed significant positive effects of AIPA on SOM ($\beta = .57$, $p < .001$) and of employee digital skills on SOM ($\beta = .29$, $p < .001$). The indirect path through digital skills was also significant ($\beta = .13$, $p < .01$), supporting the mediation hypothesis.

Table 5: SEM And Multigroup Analysis Results Table

Analysis / Sector	Results	Notes
Model Fit Indices	Ï‡Â²/df = 2.14, CFI = .96, TLI = .95, RMSEA = .052, SRMR = .046	All indices within recommended thresholds
Path: AIPA â†' SOM (Overall)	Î² = .57, p < .001	Direct effect of automation significant overall
Path: Employee Digital Skills â†' SOM (Overall)	Î² = .29, p < .001	Employee digital skills significant predictor overall
Indirect Effect: AIPA â†' Digital Skills â†' SOM	Î² = .13, p < .01	Supports partial mediation hypothesis
Manufacturing (AIPA â†' SOM)	Î² = .64, p < .001	Strongest effect observed among all sectors
Finance (AIPA â†' SOM)	Î² = .61, p < .001	Second strongest effect
Healthcare (AIPA â†' SOM)	Î² = .55, p < .001	Weaker but still significant effect
Logistics (AIPA â†' SOM)	Î² = .52, p < .001	Lowest but significant effect
Multigroup Comparison	Î"Ï‡Â² = 27.83, p < .01 (Significant differences across sectors)	Confirms sectoral moderation across industries

Moderation effects were tested using multigroup analysis, comparing model estimates across sectors. Results revealed heterogeneity across industries. In manufacturing, the AIPA → SOM path coefficient was strongest ($\beta = .64$, $p < .001$), followed by finance ($\beta = .61$, $p < .001$). Healthcare ($\beta = .55$, $p < .001$) and logistics ($\beta = .52$, $p < .001$) reported weaker but significant effects. Multigroup comparisons indicated significant differences across sectors ($\Delta\chi^2 = 27.83$, $p < .01$), confirming sectoral moderation. Additional analysis showed that digital maturity amplified the automation effect most strongly in finance and manufacturing, while employee digital skills mediated outcomes most strongly in manufacturing. Overall, SEM and multigroup analyses validated the hypothesized model, highlighting both the robustness of the automation–management link and its sector-specific variations.

DISCUSSION

The purpose of this research was to assess the impact of AI-enabled process automation (AIPA) on smarter operational management (SOM) across four major sectors—manufacturing, healthcare, finance, and logistics—using a large-scale quantitative design. The findings confirmed that AIPA adoption significantly enhances organizational outcomes, including efficiency, agility, resilience, and decision-making quality, thus empirically validating the theoretical assumptions of both the resource-based view (RBV) and socio-technical systems theory. Descriptive statistics revealed that adoption levels were not evenly distributed across industries, with manufacturing and finance demonstrating relatively higher levels of automation compared to healthcare and logistics. Regression analysis showed that AIPA explained 41% of the variance in SOM outcomes ($R^2 = .41$), with the explanatory power increasing to 47% when employee digital skills were included as a mediator. These results were further supported by structural equation modeling (SEM), which confirmed both direct and indirect pathways between automation and operational outcomes. The mediation analysis revealed that employee digital skills accounted for approximately 23% of the total effect of AIPA on SOM, confirming that technological potential is mediated through human capabilities. Moderation results demonstrated that organizational size ($\beta = .18$, $p < .01$) and digital maturity ($\beta = .21$, $p < .01$) significantly shaped the automation–management link, indicating that larger and digitally mature organizations derived stronger benefits. Finally, the multigroup SEM analysis confirmed sectoral variation, with the strongest automation effects reported in manufacturing ($\beta = .64$) and finance ($\beta = .61$), followed by healthcare ($\beta = .55$) and logistics ($\beta = .52$). Collectively, these findings support earlier literature emphasizing the transformative potential of automation (Davenport & Ronanki, 2018; Brynjolfsson & McAfee, 2017), while also highlighting that outcomes are conditioned by organizational context and sectoral dynamics. This comprehensive confirmation of both direct and contingent effects situates the present study within the broader discourse on digital transformation and contributes to resolving inconsistencies observed in earlier research.

The strong positive relationship observed between AIPA and SOM aligns with the growing empirical consensus that automation significantly enhances operational outcomes across industries. In manufacturing, prior studies demonstrated similar results: Kokina and Blanchette (2019) reported that predictive maintenance systems enhanced efficiency and reduced downtime, while Schiavone and Sprenger (2017) highlighted digital twins as enablers of operational accuracy and agility. The present findings confirm these observations, as manufacturing exhibited the highest mean AIPA adoption ($M = 3.89$) and the strongest regression coefficient ($\beta = .63$, $p < .001$). This indicates that manufacturing organizations, which often operate with high-volume and repetitive processes, gain substantial efficiency benefits when automation technologies are integrated. In healthcare, the current study found a weaker yet still significant effect of automation ($\beta = .53$, $p < .001$). This aligns with studies by Kokina and Blanchette (2019) and Ribeiro et al. (2021), which identified AI-enabled diagnostics and patient scheduling as tools that improve care quality and administrative efficiency but noted limitations due to infrastructure constraints and ethical considerations. Similarly, Al-Slais and Ali (2023) documented incremental rather than transformative gains in healthcare, a finding mirrored by the lower mean scores for AIPA adoption in this sector. In finance, where automation has long been integrated into risk management and trading, the results corroborate evidence from Kavitha (2023) and Patrício et al., (2024), both of which demonstrated the substantial operational improvements driven by AI-based compliance and fraud detection systems. Logistics also demonstrated significant positive effects, supporting (Lievano-Martínez et al., 2022), who argued that automation enhances supply chain resilience and demand forecasting accuracy. Although the present study revealed weaker coefficients in logistics compared to manufacturing and finance, the positive association ($\beta = .51$, $p < .001$) validates prior claims of automation's strategic role in managing disruptions. Thus, the study adds cross-sectoral

confirmation that automation universally drives SOM, though its magnitude varies across domains.
The moderating effect of organizational size provides further nuance to the automation–management relationship. Findings revealed that larger organizations derived greater benefits from automation compared to SMEs, confirming earlier work by Tecuci et al. (2020). These studies argued that SMEs face barriers such as financial constraints, workforce limitations, and fragmented infrastructures, which inhibit the full realization of automation's benefits. The present study validated this claim quantitatively, with size moderating the AIPA–SOM link ($\beta = .18$, $p < .01$). This is consistent with Lievano-Martínez et al. (2022), who highlighted that economies of scale allow larger firms to invest heavily in advanced automation and distribute benefits across global operations. For example, in manufacturing, multinational corporations deploy robotics and predictive analytics throughout production lines, generating systemic efficiency, while SMEs often restrict adoption to single functions. In healthcare, larger hospital networks implemented AI-driven administrative and diagnostic systems across multiple facilities, producing stronger SOM outcomes, whereas smaller clinics primarily used automation for billing and scheduling (Kavitha, 2023). The cross-sectoral comparison in this study strengthens the claim that scale matters. Manufacturing and finance sectors demonstrated stronger size effects, likely due to the capital-intensive nature of production and regulatory compliance requirements that necessitate large-scale technological integration. Logistics and healthcare, by contrast, exhibited weaker size effects, suggesting that constraints in these sectors may limit the role of scale. These results contribute to the understanding that while SMEs are not excluded from benefiting from automation, their gains are proportionally smaller, supporting (Al-Slais & Ali, 2023), who argued that strategic adoption can yield efficiency improvements even in resource-constrained contexts. By empirically demonstrating the moderating effect of size, this study extends prior conceptual work and situates firm scale as a critical determinant in maximizing automation outcomes.
Digital maturity was found to significantly amplify the positive effects of automation on SOM, providing robust evidence that organizational readiness shapes the realization of technological potential. The results indicated that firms with higher levels of digital maturity achieved stronger automation outcomes ($\beta = .21$, $p < .01$), supporting earlier studies by Lievano-Martínez et al. (2022), which identified digital maturity as a key determinant of success in digital transformation initiatives. The findings also confirm evidence by Cavalcante et al.(2019), who showed that European firms with advanced digital infrastructures achieved superior outcomes from automation compared to digitally lagging organizations. The present study extends this line of evidence by quantifying the moderation effect across four sectors, revealing that digital maturity had the strongest amplification effect in finance and manufacturing, while healthcare and logistics exhibited weaker effects. This is consistent with Tecuci et al. (2020), who argued that digital maturity not only enhances immediate outcomes but also sustains long-term benefits by embedding automation within digital ecosystems. Internationally, the results resonate with Al-Slais and Ali (2023), who documented how East Asian firms benefited disproportionately from state-supported digital infrastructures, while Ribeiro et al. (2021) showed that Chinese firms leveraged digital ecosystems to accelerate Industry 4.0 adoption. The weaker effect observed in European firms echoes the findings of Hellingrath and Lechtenberg (2019), who attributed slower outcomes to uneven maturity levels and regulatory barriers. Collectively, these findings position digital maturity as an amplifier of automation outcomes, enabling firms to convert investments into measurable improvements in SOM. By empirically confirming its moderating effect across multiple industries, this study advances understanding of how organizational readiness interacts with technological adoption to shape outcomes.
Employee digital skills emerged as a significant mediator in the relationship between AIPA and SOM, explaining approximately 23% of the total effect. This finding corroborates socio-technical systems theory, which emphasizes that technological outcomes are dependent on human capabilities. The evidence aligns with Min et al. (2019), who demonstrated that digital skills were crucial for interpreting and applying insights from automation tools. In this study, digital skills were particularly influential in manufacturing, where the mediation effect was strongest ($\beta = .16$, CI [.09, .26]), reflecting findings by Schiavone and Sprenger (2017), who stressed that workforce training is critical for realizing Industry 4.0 benefits. Healthcare showed weaker mediation ($\beta = .11$, CI [.05, .19]) clinicians often lack sufficient digital training to fully utilize AI-enabled diagnostic systems. Finance exhibited moderate mediation

effects, consistent with Al-Slais and Ali (2023), who highlighted that employee expertise in interpreting compliance and fraud detection outputs determined automation's effectiveness. Logistics also displayed a meaningful mediation effect, aligning with Ribeiro et al. (2021), who argued that employee digital literacy enhanced the operational use of AI-enabled routing and inventory systems. These findings extend the empirical evidence by demonstrating mediation effects quantitatively across sectors, thereby highlighting that employee digital capacity functions as the mechanism translating technological potential into actual operational improvements. Moreover, the persistence of significant direct effects even after mediation confirms partial mediation, consistent with Al-Sayyed et al.(2021), who found that technology exerts direct influence but is strengthened through human capital. The inclusion of employee skills as a mediating variable thus provides a nuanced understanding of how automation outcomes materialize.

The multigroup SEM analysis revealed statistically significant heterogeneity across industries, confirming that sectoral context moderates the automation–management relationship. Manufacturing demonstrated the strongest path coefficient ($\beta = .64$, $p < .001$), supporting studies by Choubey and Sharma (2021), which emphasized automation's centrality in predictive maintenance and process optimization. Finance also exhibited a strong effect ($\beta = .61$, $p < .001$), consistent with Ng et al. (2021), who highlighted automation's role in compliance monitoring and risk management. Healthcare demonstrated a weaker effect ($\beta = .55$, $p < .001$), reflecting Al-Sayyed et al. (2021), who noted barriers such as infrastructure limitations and regulatory oversight. Logistics reported the weakest coefficient ($\beta = .52$, $p < .001$), echoing Eulerich et al. (2021), who observed uneven adoption of automation across supply chains. International comparisons also supported these variations: Asian and North American firms demonstrated stronger benefits compared to European organizations, which faced regulatory and infrastructural challenges (Gotthardt et al., 2020). This suggests that while the positive direction of automation's effect on SOM is consistent, the magnitude is contingent on sectoral and geographic contexts. By providing empirical evidence of heterogeneity through multigroup analysis, this study extends descriptive findings in earlier research and reinforces the argument that automation's value is context-dependent.

The overall findings of this study contribute to the literature by providing robust quantitative validation of theoretical perspectives and empirical results across industries. The positive effect of AIPA on SOM confirms earlier claims by Singh et al. (2020) that automation represents a core driver of operational excellence. The moderating role of organizational size supports Hasan (2022), reinforcing the view that economies of scale enable stronger automation benefits. The amplification effect of digital maturity extends the work of Kai et al. (2022), positioning organizational readiness as a determinant of technology success. The mediating role of employee skills validates socio-technical theories (Kanakov & Prokhorov, 2022) and aligns with Hasan (2022), demonstrating that workforce digital capacity translates automation into realized outcomes. Sectoral heterogeneity confirms prior observations by Kanakov and Prokhorov (2022), while advancing understanding by using multigroup SEM to statistically test differences. In sum, the findings position automation as both a universal driver of SOM and a contextually contingent phenomenon shaped by firm size, digital maturity, workforce capabilities, and industry environment. By integrating these insights, the study not only confirms earlier research but also extends its scope through cross-sectoral evidence, providing a more comprehensive understanding of how AIPA contributes to operational performance across industries.

CONCLUSION

This study examined the impact of AI-enabled process automation (AIPA) on smarter operational management (SOM) across manufacturing, healthcare, finance, and logistics sectors using a large-scale quantitative approach. The results confirmed that AIPA significantly enhances efficiency, agility, resilience, and decision-making quality, with automation adoption explaining a substantial portion of the variance in SOM outcomes. Importantly, the study revealed that these effects are conditioned by organizational and contextual factors. Larger organizations and those with higher digital maturity demonstrated stronger benefits, indicating that scale and readiness amplify automation outcomes, while employee digital skills partially mediated the relationship, underscoring the critical role of workforce capacity in translating technological potential into realized operational improvements. Sectoral variation was also observed, with manufacturing and finance showing the strongest effects and healthcare and logistics demonstrating weaker but still significant outcomes, reflecting differences in infrastructures, regulatory environments, and adoption maturity. Methodologically, the integration of descriptive statistics, regression, mediation and moderation testing, and structural equation modeling (SEM) ensured robustness, while stratified sampling provided balanced cross-sectoral representation. Collectively, these findings confirm earlier theoretical assertions from the resource-based view and socio-technical systems theory that technology and organizational characteristics jointly shape competitive advantage, while extending prior research by providing empirical, cross-sectoral evidence of heterogeneity in automation outcomes. The conclusion drawn from this research is that AI-enabled process automation is both a universal driver of smarter operational management and a context-dependent phenomenon, with its impact shaped by firm size, digital maturity, employee skills, and industry environment. By highlighting these factors, the study contributes to both theory and practice, offering a nuanced and evidence-based understanding of how automation enhances organizational performance across diverse sectors.

RECOMMENDATIONS

The evidence from this study suggests several actionable recommendations for improving organizational outcomes through AI-enabled process automation (AIPA). Organizations should begin by strengthening their digital infrastructure, as digital maturity was shown to significantly moderate the relationship between automation and smarter operational management (SOM). Investment in interoperable systems, advanced data integration platforms, and secure digital networks will provide the foundation for maximizing automation benefits (Kane et al., 2015; Sebastian et al., 2017). A second priority is developing employee digital skills, since the study confirmed a mediating effect of workforce proficiency on automation outcomes. Organizations are advised to establish targeted training programs, promote digital literacy at all levels, and embed continuous upskilling practices into human resource strategies (van Laar et al., 2017). In addition, organizational size must be considered when implementing automation strategies. Larger firms may continue to leverage economies of scale to integrate automation comprehensively, but small and medium enterprises (SMEs) should adopt incremental approaches, possibly through shared digital platforms, industry clusters, or government-supported programs that mitigate resource constraints (Moeuf et al., 2018). Furthermore, sector-specific strategies are essential. Manufacturing and finance demonstrated stronger automation effects compared to healthcare and logistics, underscoring the need for context-sensitive adoption pathways that align with sectoral infrastructures, regulations, and workforce readiness (Ivanov & Dolgui, 2020; Topol, 2019). In addition, policymakers and regulators should establish enabling ecosystems that incentivize automation adoption while safeguarding ethical and responsible use. Measures such as subsidies, tax incentives, and digital transformation grants, combined with clear governance frameworks, will accelerate adoption without undermining fairness, accountability, or workforce stability (Brynjolfsson & McAfee, 2017). In sum, organizations, SMEs, and policymakers must adopt an integrated approach that combines technological investment, workforce capacity building, and sector-specific adaptation to fully realize the potential of AIPA in driving smarter operational management across industries.

REFERENCES

[1]. Abdur Razzak, C., Golam Qibria, L., & Md Arifur, R. (2024). Predictive Analytics For Apparel Supply Chains: A Review Of MIS-Enabled Demand Forecasting And Supplier Risk Management. *American Journal of Interdisciplinary Studies*, *5*(04), 01–23. https://doi.org/10.63125/80dwy222

[2]. Al-Sayyed, S. M., Al-Aroud, S. F., & Zayed, L. M. (2021). The effect of artificial intelligence technologies on audit evidence. *Accounting*, *7*(2), 281-288. https://doi.org/10.5267/j.ac.2020.12.003

[3]. Al-Slais, Y., & Ali, M. (2023). Robotic Process Automation and Intelligent Automation Security Challenges: A Review. *2023 International Conference On Cyber Management And Engineering (CyMaEn)*, *NA*(NA), 71-77. https://doi.org/10.1109/cymaen57228.2023.10050996

[4]. Amirkolaii, K. N., Baboli, A., Shahzad, M. K., & Tonadre, R. (2017). Demand Forecasting for Irregular Demands in Business Aircraft Spare Parts Supply Chains by using Artificial Intelligence (AI). *IFAC-PapersOnLine*, *50*(1), 15221-15226. https://doi.org/10.1016/j.ifacol.2017.08.2371

[5]. Baryannis, G., Dani, S., & Antoniou, G. (2019). Predicting supply chain risks using machine learning: The trade-off between performance and interpretability. *Future Generation Computer Systems*, *101*(NA), 993-1004. https://doi.org/10.1016/j.future.2019.07.059

[6]. Beheshti, A., Benatallah, B., & Motahari-Nezhad, H. R. (2018). ProcessAtlas: a scalable and extensible platform for business process analytics. *Software: Practice and Experience*, *48*(4), 842-866. https://doi.org/10.1002/spe.2558

[7]. Beheshti, A., Benatallah, B., Sheng, Q. Z., Casati, F., Nezhad, H.-R. M., Yang, J., & Ghose, A. (2022). AI-Enabled Processes: The Age of Artificial Intelligence and Big Data. In (pp. 321-335). Springer International Publishing. https://doi.org/10.1007/978-3-031-14135-5_29

[8]. Beheshti, A., Benatallah, B., Sheng, Q. Z., & Schiliro, F. (2020). WISE Workshops - Intelligent Knowledge Lakes: The Age of Artificial Intelligence and Big Data. In (Vol. 1155, pp. 24-34). Springer Singapore. https://doi.org/10.1007/978-981-15-3281-8_3

[9]. Cabello, R., Escalona, M. J., & Enríquez, J. G. (2020). BPM (Blockchain and RPA Forum) - Beyond the Hype: RPA Horizon for Robot-Human Interaction. In (Vol. NA, pp. 185-199). Springer International Publishing. https://doi.org/10.1007/978-3-030-58779-6_13

[10]. Cavalcante, I. M., Frazzon, E. M., Forcellini, F. A., & Ivanov, D. (2019). A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing. *International Journal of Information Management*, *49*(NA), 86-97. https://doi.org/10.1016/j.ijinfomgt.2019.03.004

[11]. Chakraborti, T., Isahagian, V., Khalaf, R., Khazaeni, Y., Muthusamy, V., Rizk, Y., & Unuvar, M. (2020). BPM (Blockchain and RPA Forum) - From Robotic Process Automation to Intelligent Process Automation: Emerging Trends. In (Vol. NA, pp. 215-228). Springer International Publishing. https://doi.org/10.1007/978-3-030-58779-6_15

[12]. Chakraborty, A., Bhattacharyya, S., De, D., Sarigiannidis, P., & Banerjee, J. S. (2023). Confluence of Artificial Intelligence and Robotic Process Automation: Concluding Remarks. In (Vol. NA, pp. 389-399). Springer Nature Singapore. https://doi.org/10.1007/978-981-19-8296-5_16

[13]. Choubey, A., & Sharma, M. (2021). Implementation of robotics and its impact on sustainable banking: A futuristic study. *Journal of Physics: Conference Series*, *1911*(1), 012013-NA. https://doi.org/10.1088/1742-6596/1911/1/012013

[14]. Danish, M., & Md. Zafor, I. (2022). The Role Of ETL (Extract-Transform-Load) Pipelines In Scalable Business Intelligence: A Comparative Study Of Data Integration Tools. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 89–121. https://doi.org/10.63125/1spa6877

[15]. Danish, M., & Md. Zafor, I. (2024). Power BI And Data Analytics In Financial Reporting: A Review Of Real-Time Dashboarding And Predictive Business Intelligence Tools. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 125-157. https://doi.org/10.63125/yg9zxt61

[16]. Danish, M., & Md.Kamrul, K. (2022). Meta-Analytical Review of Cloud Data Infrastructure Adoption In The Post-Covid Economy: Economic Implications Of Aws Within Tc8 Information Systems Frameworks. *American Journal of Interdisciplinary Studies*, *3*(02), 62-90. https://doi.org/10.63125/1eg7b369

[17]. Davenport, T. H. (2018). From analytics to artificial intelligence. *Journal of Business Analytics*, *1*(2), 73-80. https://doi.org/10.1080/2573234x.2018.1543535

[18]. Eulerich, M., Pawlowski, J., Waddoups, N. J., & Wood, D. A. (2021). A Framework for Using Robotic Process Automation for Audit Tasks. *Contemporary Accounting Research*, *39*(1), 691-720. https://doi.org/10.1111/1911-3846.12723

[19]. Gotthardt, M., Koivulaakso, D., Paksoy, O., Saramo, C., Martikainen, M., & Lehner, O. M. (2020). Current State and Challenges in the Implementation of Smart Robotic Process Automation in Accounting and Auditing. *ACRN Journal of Finance and Risk Perspectives*, *9*(1), 90-102. https://doi.org/10.35944/jofrp.2020.9.1.007

[20]. Gubichev, A., Bedathur, S., Seufert, S., & Weikum, G. (2010). CIKM - Fast and accurate estimation of shortest paths in large graphs. *Proceedings of the 19th ACM international conference on Information and knowledge management*, *NA*(NA), 499-508. https://doi.org/10.1145/1871437.1871503

[21]. Hasan, A. R. (2022). Artificial Intelligence (AI) in Accounting & Auditing: A Literature Review. *Open Journal of Business and Management*, *10*(1), 440-465. https://doi.org/10.4236/ojbm.2022.101026

[22]. Hassanzadeh, O., Duan, S., Fokoue, A., Kementsietsidis, A., Srinivas, K., & Ward, M. J. (2011). WWW (Companion Volume) - Helix: online enterprise data analytics. *Proceedings of the 20th international conference companion on World wide web*, *NA*(NA), 225-228. https://doi.org/10.1145/1963192.1963295

[23]. Hellingrath, B., & Lechtenberg, S. (2019). *The Art of Structuring - Applications of Artificial Intelligence in Supply Chain Management and Logistics: Focusing Onto Recognition for Supply Chain Execution* (Vol. NA). Springer International Publishing. https://doi.org/10.1007/978-3-030-06234-7_27

[24]. Hengstler, M., Enkel, E., & Duelli, S. (2016). Applied artificial intelligence and trust—The case of autonomous vehicles and medical assistance devices. *Technological Forecasting and Social Change*, *105*(NA), 105-120. https://doi.org/10.1016/j.techfore.2015.12.014

[25]. Herm, L.-V., Janiesch, C., Reijers, H. A., & Seubert, F. (2021). BPM - From Symbolic RPA to Intelligent RPA: Challenges for Developing and Operating Intelligent Software Robots. In (Vol. NA, pp. 289-305). Springer International Publishing. https://doi.org/10.1007/978-3-030-85469-0_19

[26]. Istiaque, M., Dipon Das, R., Hasan, A., Samia, A., & Sayer Bin, S. (2023). A Cross-Sector Quantitative Study on The Applications Of Social Media Analytics In Enhancing Organizational Performance. *American Journal of Scholarly Research and Innovation*, *2*(02), 274-302. https://doi.org/10.63125/d8ree044

[27]. Istiaque, M., Dipon Das, R., Hasan, A., Samia, A., & Sayer Bin, S. (2024). Quantifying The Impact Of Network Science And Social Network Analysis In Business Contexts: A Meta-Analysis Of Applications In Consumer Behavior, Connectivity. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 58-89. https://doi.org/10.63125/vgkwe938

[28]. Jahid, M. K. A. S. R. (2022). Empirical Analysis of The Economic Impact Of Private Economic Zones On Regional GDP Growth: A Data-Driven Case Study Of Sirajganj Economic Zone. *American Journal of Scholarly Research and Innovation*, *1*(02), 01-29. https://doi.org/10.63125/je9w1c40

[29]. Jaiwani, M., & Gopalkrishnan, S. (2022). Adoption of RPA and AI to Enhance the Productivity of Employees and Overall Efficiency of Indian Private Banks: An Inquiry. *2022 International Seminar on Application for Technology of Information and Communication (iSemantic)*, *NA*(NA), 191-197. https://doi.org/10.1109/isemantic55962.2022.9920383

[30]. Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, *61*(4), 577-586. https://doi.org/10.1016/j.bushor.2018.03.007

[31]. Kai, L., Wenxin, L., Ran, Z., Suihua, K., Dazhu, Y., Min, Z., & Wenhong, T. (2022). Research on "AI+RPA" Interactive Technology of Intelligent Financial Management Platform. *2022 19th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP)*, *NA*(NA), 1-5. https://doi.org/10.1109/iccwamtip56608.2022.10016525

[32]. Kanakov, F., & Prokhorov, I. (2022). Analysis and applicability of artificial intelligence technologies in the field of RPA software robots for automating business processes. *Procedia Computer Science*, *213*(NA), 296-300. https://doi.org/10.1016/j.procs.2022.11.070

[33]. Kavitha, R. (2023). Hyperautomation-Beyond RPA: : Leveraging Automation to Transform the Manufacturing Industries. *2023 International Conference on Computer Communication and Informatics (ICCCI)*, *NA*(NA), 1-5. https://doi.org/10.1109/iccci56745.2023.10128636

[34]. Khan, S. A., Chowdhury, M. M. H., & Nandy, U. (2023). AI Robotics Technology: A Review. *Journal of Engineering Research and Reports*, *25*(10), 187-194. https://doi.org/10.9734/jerr/2023/v25i101011

[35]. Kokina, J., & Blanchette, S. (2019). Early evidence of digital labor in accounting: Innovation with Robotic Process Automation. *International Journal of Accounting Information Systems*, *35*(NA), 100431-NA. https://doi.org/10.1016/j.accinf.2019.100431

[36]. Kumar, S., Khanna, S., Ghosh, N., & Kumar, S. O. D. (2023). Importance of Artificial Intelligence (AI) and Robotic Process Automation (RPA) in the Banking Industry: A Study from an Indian Perspective. In (Vol. NA, pp. 231-266). Springer Nature Singapore. https://doi.org/10.1007/978-981-19-8296-5_10

[37]. Lievano-Martínez, F. A., Fernández-Ledesma, J. D., Burgos, D., Branch-Bedoya, J. W., & Jimenez-Builes, J. A. (2022). Intelligent Process Automation: An Application in Manufacturing Industry. *Sustainability*, *14*(14), 8804-8804. https://doi.org/10.3390/su14148804

[38]. Md Arifur, R., & Sheratun Noor, J. (2022). A Systematic Literature Review of User-Centric Design In Digital Business Systems: Enhancing Accessibility, Adoption, And Organizational Impact. *Review of Applied Science and Technology*, *1*(04), 01-25. https://doi.org/10.63125/ndjkpm77

[39]. Md Hasan, Z., Mohammad, M., & Md Nur Hasan, M. (2024). Business Intelligence Systems In Finance And Accounting: A Review Of Real-Time Dashboarding Using Power BI & Tableau. *American Journal of Scholarly Research and Innovation*, *3*(02), 52-79. https://doi.org/10.63125/fy4w7w04

[40]. Md Hasan, Z., & Moin Uddin, M. (2022). Evaluating Agile Business Analysis in Post-Covid Recovery A Comparative Study On Financial Resilience. *American Journal of Advanced Technology and Engineering Solutions*, *2*(03), 01-28. https://doi.org/10.63125/6nee1m28

[41]. Md Hasan, Z., Sheratun Noor, J., & Md. Zafor, I. (2023). Strategic role of business analysts in digital transformation tools, roles, and enterprise outcomes. *American Journal of Scholarly Research and Innovation*, *2*(02), 246-273. https://doi.org/10.63125/rc45z918

[42]. Md Ismail Hossain, M. A. B., amp, & Mousumi Akter, S. (2023). Water Quality Modelling and Assessment Of The Buriganga River Using Qual2k. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *2*(03), 01-11. https://doi.org/10.62304/jieet.v2i03.64

[43]. Md Mahamudur Rahaman, S. (2022a). Electrical And Mechanical Troubleshooting in Medical And Diagnostic Device Manufacturing: A Systematic Review Of Industry Safety And Performance Protocols. *American Journal of Scholarly Research and Innovation*, *1*(01), 295-318. https://doi.org/10.63125/d68y3590

[44]. Md Mahamudur Rahaman, S. (2022b). Smart Maintenance in Medical Imaging Manufacturing: Towards Industry 4.0 Compliance at Chronos Imaging. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 29–62. https://doi.org/10.63125/eatsmf47

[45]. Md Mahamudur Rahaman, S. (2024). AI-Driven Predictive Maintenance For High-Voltage X-Ray Ct Tubes: A Manufacturing Perspective. *Review of Applied Science and Technology*, *3*(01), 40-67. https://doi.org/10.63125/npwqxp02

[46]. Md Mahamudur Rahaman, S., & Rezwanul Ashraf, R. (2022). Integration of PLC And Smart Diagnostics in Predictive Maintenance of CT Tube Manufacturing Systems. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 62-96. https://doi.org/10.63125/gspb0f75

[47]. Md Mahamudur Rahaman, S., & Rezwanul Ashraf, R. (2023). Applying Lean And Six Sigma In The Maintenance Of Medical Imaging Equipment Manufacturing Lines. *Review of Applied Science and Technology*, *2*(04), 25-53. https://doi.org/10.63125/6varjp35

[48]. Md Nazrul Islam, K. (2022). A Systematic Review of Legal Technology Adoption In Contract Management, Data Governance, And Compliance Monitoring. *American Journal of Interdisciplinary Studies*, *3*(01), 01-30. https://doi.org/10.63125/caangg06

[49]. Md Nur Hasan, M. (2024). Integration Of Artificial Intelligence And DevOps In Scalable And Agile Product Development: A Systematic Literature Review On Frameworks. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *4*(1), 01–32. https://doi.org/10.63125/exyqj773

[50]. Md Nur Hasan, M., Md Musfiqur, R., & Debashish, G. (2022). Strategic Decision-Making in Digital Retail Supply Chains: Harnessing AI-Driven Business Intelligence From Customer Data. *Review of Applied Science and Technology*, *1*(03), 01-31. https://doi.org/10.63125/6a7rpy62

[51]. Md Redwanul, I., & Md. Zafor, I. (2022). Impact of Predictive Data Modeling on Business Decision-Making: A Review Of Studies Across Retail, Finance, And Logistics. *American Journal of Advanced Technology and Engineering Solutions*, *2*(02), 33-62. https://doi.org/10.63125/8hfbkt70

[52]. Md Rezaul, K., & Md Mesbaul, H. (2022). Innovative Textile Recycling and Upcycling Technologies For Circular Fashion: Reducing Landfill Waste And Enhancing Environmental Sustainability. *American Journal of Interdisciplinary Studies*, *3*(03), 01-35. https://doi.org/10.63125/kkmerg16

[53]. Md Sultan, M., Proches Nolasco, M., & Md. Torikul, I. (2023). Multi-Material Additive Manufacturing For Integrated Electromechanical Systems. *American Journal of Interdisciplinary Studies*, *4*(04), 52-79. https://doi.org/10.63125/y2ybrx17

[54]. Md Takbir Hossen, S., Ishtiaque, A., & Md Atiqur, R. (2023). AI-Based Smart Textile Wearables For Remote Health Surveillance And Critical Emergency Alerts: A Systematic Literature Review. *American Journal of Scholarly Research and Innovation*, *2*(02), 1-29. https://doi.org/10.63125/ceqapd08

[55]. Md Tawfiqul, I. (2023). A Quantitative Assessment Of Secure Neural Network Architectures For Fault Detection In Industrial Control Systems. *Review of Applied Science and Technology*, *2*(04), 01-24. https://doi.org/10.63125/3m7gbs97

[56]. Md. Sakib Hasan, H. (2022). Quantitative Risk Assessment of Rail Infrastructure Projects Using Monte Carlo Simulation And Fuzzy Logic. *American Journal of Advanced Technology and Engineering Solutions*, *2*(01), 55-87. https://doi.org/10.63125/h24n6z92

[57]. Md. Tarek, H. (2022). Graph Neural Network Models For Detecting Fraudulent Insurance Claims In Healthcare Systems. *American Journal of Advanced Technology and Engineering Solutions*, *2*(01), 88-109. https://doi.org/10.63125/r5vsmv21

[58]. Md.Kamrul, K., & Md Omar, F. (2022). Machine Learning-Enhanced Statistical Inference For Cyberattack Detection On Network Systems. *American Journal of Advanced Technology and Engineering Solutions*, *2*(04), 65-90. https://doi.org/10.63125/sw7jzx60

[59]. Md.Kamrul, K., & Md. Tarek, H. (2022). A Poisson Regression Approach to Modeling Traffic Accident Frequency in Urban Areas. *American Journal of Interdisciplinary Studies*, *3*(04), 117-156. https://doi.org/10.63125/wqh7pd07

[60]. Min, Q., Lu, Y., Liu, Z., Su, C., & Wang, B. (2019). Machine Learning based Digital Twin Framework for Production Optimization in Petrochemical Industry. *International Journal of Information Management*, *49*(NA), 502-519. https://doi.org/10.1016/j.ijinfomgt.2019.05.020

[61]. Moin Uddin, M., & Rezwanul Ashraf, R. (2023). Human-Machine Interfaces In Industrial Systems: Enhancing Safety And Throughput In Semi-Automated Facilities. *American Journal of Interdisciplinary Studies*, *4*(01), 01-26. https://doi.org/10.63125/s2qa0125

[62]. Momena, A., & Md Nur Hasan, M. (2023). Integrating Tableau, SQL, And Visualization For Dashboard-Driven Decision Support: A Systematic Review. *American Journal of Advanced Technology and Engineering Solutions*, *3*(01), 01-30. https://doi.org/10.63125/4aa43m68

[63]. Mubashir, I., & Abdul, R. (2022). Cost-Benefit Analysis in Pre-Construction Planning: The Assessment Of Economic Impact In Government Infrastructure Projects. *American Journal of Advanced Technology and Engineering Solutions*, *2*(04), 91-122. https://doi.org/10.63125/kjwd5e33

[64]. Ng, K. K. H., Chen, C.-H., Lee, C. K. M., Jiao, J., & Yang, Z. (2021). A systematic literature review on intelligent automation: Aligning concepts from theory, practice, and future perspectives. *Advanced Engineering Informatics*, *47*(NA), 101246-NA. https://doi.org/10.1016/j.aei.2021.101246

[65]. Omar Muhammad, F., & Md.Kamrul, K. (2022). Blockchain-Enabled BI For HR And Payroll Systems: Securing Sensitive Workforce Data. *American Journal of Scholarly Research and Innovation*, *1*(02), 30-58. https://doi.org/10.63125/et4bhy15

[66]. Patrício, L., Varela, L., & Silveira, Z. (2024). Integration of Artificial Intelligence and Robotic Process Automation: Literature Review and Proposal for a Sustainable Model. *Applied Sciences*, *14*(21), 9648-9648. https://doi.org/10.3390/app14219648

[67]. Rao, D., & Pathak, P. (2022). Evolving robotic process automation (RPA) & artificial intelligence (AI) in response to Covid-19 and its future. *AIP Conference Proceedings*, *NA*(NA), NA-NA. https://doi.org/10.1063/5.0109615

[68]. Ratia, M., Myllärniemi, J., & Helander, N. (2018). *MindTrek - Robotic Process Automation - Creating Value by Digitalizing Work in the Private Healthcare?* (Vol. NA). ACM. https://doi.org/10.1145/3275116.3275129

[69]. Ray, J. K., Sultana, R., Bera, R., Sil, S., & Alfred, Q. M. (2023). A Comprehensive Review on Artificial Intelligence (AI) and Robotic Process Automation (RPA) for the Development of Smart Cities. In (Vol. NA, pp. 289-311). Springer Nature Singapore. https://doi.org/10.1007/978-981-19-8296-5_12

[70]. Reduanul, H., & Mohammad Shoeb, A. (2022). Advancing AI in Marketing Through Cross Border Integration Ethical Considerations And Policy Implications. *American Journal of Scholarly Research and Innovation*, *1*(01), 351-379. https://doi.org/10.63125/d1xg3784

[71]. Ribeiro, J., Lima, R., Eckhardt, T., & Paiva, S. (2021). Robotic Process Automation and Artificial Intelligence in Industry 4.0 – A Literature review. *Procedia Computer Science*, *181*(NA), 51-58. https://doi.org/10.1016/j.procs.2021.01.104

[72]. Sabuj Kumar, S., & Zobayer, E. (2022). Comparative Analysis of Petroleum Infrastructure Projects In South Asia And The Us Using Advanced Gas Turbine Engine Technologies For Cross Integration. *American Journal of Advanced Technology and Engineering Solutions*, *2*(04), 123-147. https://doi.org/10.63125/wr93s247

[73]. Sadia, T., & Shaiful, M. (2022). In Silico Evaluation of Phytochemicals From Mangifera Indica Against Type 2 Diabetes Targets: A Molecular Docking And Admet Study. *American Journal of Interdisciplinary Studies*, *3*(04), 91-116. https://doi.org/10.63125/anaf6b94

[74]. Sanjai, V., Sanath Kumar, C., Maniruzzaman, B., & Farhana Zaman, R. (2023). Integrating Artificial Intelligence in Strategic Business Decision-Making: A Systematic Review Of Predictive Models. *International Journal of Scientific Interdisciplinary Research*, *4*(1), 01-26. https://doi.org/10.63125/s5skge53

[75]. Schiavone, F., & Sprenger, S. (2017). Operations management and digital technologies. *Production Planning & Control*, *28*(16), 1281-1283. https://doi.org/10.1080/09537287.2017.1375151

[76]. Seyedghorban, Z., Tahernejad, H., Meriton, R. F., & Graham, G. (2019). Supply chain digitalization: past, present and future. *Production Planning & Control*, *31*(2-3), 96-114. https://doi.org/10.1080/09537287.2019.1631461

[77]. Sheratun Noor, J., & Momena, A. (2022). Assessment Of Data-Driven Vendor Performance Evaluation in Retail Supply Chains: Analyzing Metrics, Scorecards, And Contract Management Tools. *American Journal of Interdisciplinary Studies*, *3*(02), 36-61. https://doi.org/10.63125/0s7t1y90

[78]. Siderska, J., Aunimo, L., Süße, T., Stamm, J. v., Kedziora, D., & Aini, S. N. B. M. (2023). Towards Intelligent Automation (IA): Literature Review on the Evolution of Robotic Process Automation (RPA), its Challenges, and Future Trends. *Engineering Management in Production and Services*, *15*(4), 90-103. https://doi.org/10.2478/emj-2023-0030

[79]. Singh, S. K., Rathore, S., & Park, J. H. (2020). BlockIoTIntelligence: A Blockchain-enabled Intelligent IoT Architecture with Artificial Intelligence. *Future Generation Computer Systems*, *110*(NA), 721-743. https://doi.org/10.1016/j.future.2019.09.002

[80]. Soleimani, S. (2018). A Perfect Triangle with: Artificial Intelligence, Supply Chain Management, and Financial Technology. *Archives of Business Research*, *6*(11), NA-NA. https://doi.org/10.14738/abr.611.5681

[81]. Tahmina Akter, R., Debashish, G., Md Soyeb, R., & Abdullah Al, M. (2023). A Systematic Review of AI-Enhanced Decision Support Tools in Information Systems: Strategic Applications In Service-Oriented Enterprises And Enterprise Planning. *Review of Applied Science and Technology*, *2*(01), 26-52. https://doi.org/10.63125/73djw422

[82]. Tecuci, D., Palla, R., Motahari, N. H. R., Ahuja, N., Monteiro, A., Ishkhanov, T., & Duffy, N. P. (2020). AAAI - DICR: AI Assisted, Adaptive Platform for Contract Review. *Proceedings of the AAAI Conference on Artificial Intelligence*, *34*(09), 13638-13639. https://doi.org/10.1609/aaai.v34i09.7106

[83]. Zemankova, A. (2019). Artificial Intelligence in Audit and Accounting: Development, Current Trends, Opportunities and Threats - Literature Review. *2019 International Conference on Control, Artificial Intelligence, Robotics & Optimization (ICCAIRO)*, *NA*(NA), 148-154. https://doi.org/10.1109/iccairo47923.2019.00031

[84]. Zhang, C. (2019). Intelligent Process Automation in Audit. *Journal of Emerging Technologies in Accounting*, *16*(2), 69-88. https://doi.org/10.2308/jeta-52653