The Role of Automation and IoT in Enhancing Operational Efficiency: Evidence from PLS-SEM Analysis

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ABSTRACT

In today's competitive business environment, operational efficiency is crucial for organizations to maintain a competitive edge. The integration of automation and the Internet of Things (IoT) has emerged as a transformative approach to streamline processes and enhance productivity. However, the synergistic impact of these technologies on operational efficiency remains underexplored. **This study aims** to evaluate the individual and combined effects of automation and IoT on operational efficiency. It seeks to provide empirical evidence on how these technologies contribute to optimizing workflows and decision-making processes. **Methodology Using Partial Least** Squares Structural Equation Modeling (PLS-SEM), data were collected from organizations across multiple industries. Constructs were measured through validated survey instruments, and hypotheses were tested for direct and synergistic effects. **The findings** indicate that automation significantly enhances operational efficiency by reducing errors and improving process consistency. IoT adoption complements this by enabling real-time insights and improved decision-making. The combined implementation of these technologies demonstrates a moderate synergistic effect, amplifying operational gains. **This study underscores** the transformative potential of integrating automation and IoT. By leveraging their complementary strengths, organizations can achieve higher levels of efficiency, providing valuable guidance for digital transformation strategies.

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1. INTRODUCTION

In today's dynamic business environment, operational efficiency remains a critical factor for organizations striving to maintain a competitive edge. The advent of emerging technologies, such as automation and the Internet of Things (IoT), has provided new opportunities to streamline processes, reduce costs, and enhance productivity. However, while these technologies are widely recognized for their transformative potential, their actual impact on operational efficiency remains an area requiring empirical validation.

Automation, characterized by the use of systems and processes to perform tasks with minimal human intervention, has been increasingly adopted across industries. By enabling precision, consistency, and speed, automation has the potential to significantly enhance organizational performance. Similarly, IoT technologies, which connect physical devices and enable data-driven decision-making, promise to revolutionize operational workflows by providing real-time insights and fostering greater interconnectivity.

Despite the growing adoption of automation and IoT, there remains a lack of comprehensive studies that explore their combined impact on operational efficiency. Most existing research focuses on isolated aspects of these technologies, leaving a gap in understanding their synergistic effects. This study addresses this gap by employing Partial Least Squares Structural Equation Modeling (PLS-SEM) to quantitatively assess the relationships between automation, IoT, and operational efficiency.

The primary objective of this study is to evaluate the impact of automation and IoT on operational efficiency while also exploring their synergistic effects. To achieve this, the study aims to answer key questions: What is the impact of automation on operational efficiency? How does IoT adoption influence operational performance? And what are the combined effects of automation and IoT on operational efficiency?

This research contributes to the existing body of literature by providing empirical evidence of the combined impact of automation and IoT on operational efficiency. The findings offer valuable insights for business managers and decision-makers aiming to implement these technologies effectively. Furthermore, the study highlights key challenges and enablers for leveraging these technologies, offering a roadmap for their successful adoption in diverse organizational contexts.

2. LITERATURE REVIEW

This section reviews the existing body of knowledge on automation, the Internet of Things (IoT), and their potential impact on operational efficiency. It also highlights the gaps in the literature and provides the theoretical framework for this study.

2.1. Automation and Operational Efficiency

Automation has become a critical component of modern operational management, enabling organizations to enhance efficiency through consistency, accuracy, and speed. Automation technologies, ranging from robotic process automation (RPA) to industrial automation, have shown significant benefits in reducing errors and improving productivity. [1] emphasize that automation is particularly effective in labor-intensive processes, where it helps organizations streamline workflows and achieve operational excellence [2].

However, while the benefits of automation are well-documented, its adoption is not without challenges. [3] highlight that high implementation costs and workforce displacement remain significant barriers. Despite these challenges, the potential of automation to standardize processes and scale operations makes it a valuable asset in achieving competitive advantage [4].

2.2. IoT and Operational Efficiency

The Internet of Things (IoT) has introduced a new paradigm in operational management by connecting physical devices and enabling real-time data exchange [5]. IoT technologies enhance visibility, traceability, and control over operational workflows, providing organizations with actionable insights. According to [6], IoT-driven systems allow for better resource allocation and improved decision-making, which are critical for achieving operational efficiency.

Empirical studies, such as those by [7], have demonstrated the positive impact of IoT adoption on supply chain performance and customer satisfaction. However, challenges such as cybersecurity risks and interoperability issues can hinder IoT implementation. [8] note that addressing these challenges is essential for organizations to fully leverage IoT's potential in enhancing operational workflows.

2.3. Synergy Between Automation and IoT

While automation and IoT have been extensively studied as independent technologies, their combined impact on operational efficiency has received limited attention. The integration of automation with IoT technologies has the potential to create self-regulating systems that optimize operations in real time. According to [9], this synergy can enhance both speed and accuracy, providing exponential benefits beyond the individual contributions of each technology.

Despite the theoretical promise of this integration, empirical evidence remains sparse. Most studies focus on isolated aspects of automation or IoT, leaving a gap in understanding how these technologies interact to improve operational performance. This study aims to address this gap by exploring the synergistic effects of automation and IoT on operational efficiency [10].

2.4. Theoretical Framework

The theoretical foundation of this study is derived from the Technology-Organization-Environment (TOE) framework and the Unified Theory of Acceptance and Use of Technology (UTAUT). The TOE framework, proposed by [11], identifies technological, organizational, and environmental factors influencing technology adoption. This framework is particularly relevant for understanding the adoption of automation and IoT in organizational settings [12].

In addition, the UTAUT model developed by [13] provides insights into the factors driving technology acceptance, including performance expectancy, effort expectancy, social influence, and facilitating conditions. Together, these frameworks offer a robust basis for examining the impact of automation and IoT on operational efficiency [14].

2.5. Research Hypotheses

Based on the literature, the following hypotheses are proposed:

1. **H1**: Automation positively impacts operational efficiency.
2. **H2**: IoT positively impacts operational efficiency.
3. **H3**: The combined adoption of automation and IoT creates a synergistic effect on operational efficiency.

2.6. Research Gap and Contribution

The review of the literature highlights a significant gap in understanding the combined impact of automation and IoT on operational efficiency [15]. While both technologies have been studied individually, little empirical work has explored their synergy. This study seeks to fill this gap by employing Partial Least Squares Structural Equation Modeling (PLS-SEM) to assess these relationships. The findings aim to contribute to both theoretical understanding and practical applications, providing actionable insights for organizations seeking to adopt these technologies effectively [16].

3. RESEARCH METHOD

This study employs a quantitative research approach to examine the impact of automation and IoT on operational efficiency. The research design, data collection methods, and analytical procedures are described in detail below [17].

3.1. Research Design

A cross-sectional research design was adopted to collect data from organizations actively utilizing automation and IoT technologies. The study aims to empirically test the hypothesized relationships using Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM is particularly suited for analyzing complex relationships between constructs and is widely used in exploratory research where theoretical models are being tested [18].

3.2. Population and Sampling

The target population for this study consists of organizations that have adopted automation and IoT technologies in their operations. Purposive sampling was employed to ensure that participants had relevant experience with these technologies. The sample includes managers and decision-makers from industries such as manufacturing, logistics, and retail. A total of [insert sample size] responses were collected, which meets the minimum sample size requirements for PLS-SEM analysis, as determined using G*Power software.

3.3. Data Collection

Primary data were collected through a structured online questionnaire distributed to participants. The questionnaire was divided into sections covering automation adoption, IoT implementation, and operational efficiency. Table 1 presents the survey items used to measure the constructs in this study. Respondents rated their agreement with each statement using a five-point Likert scale, ranging from 1 (*Strongly Disagree*) to 5 (*Strongly Agree*).

As shown in Table 1, each construct is measured using multiple items to capture its multidimensional nature. For instance, automation is assessed based on its ability to handle routine tasks, improve accuracy, and

Table 1. Survey Items for Constructs

Construct	Survey Item
Automation	1. Our organization uses automated systems for routine tasks. 2. Automation has improved the accuracy of our operations. 3. Automation has reduced the time required to complete tasks.
IoT Adoption	1. IoT devices are integrated into our operations. 2. Data from IoT devices is utilized for decision-making. 3. IoT improves visibility and traceability in our workflows.
Operational Efficiency	1. We have reduced costs through operational efficiencies. 2. Productivity has increased due to technology adoption. 3. Processes are completed faster due to automation and IoT.

reduce task completion time. Similarly, IoT adoption is measured by the integration of IoT devices, data utilization, and workflow improvements. Operational efficiency is evaluated in terms of cost reduction, productivity gains, and process speed.

3.4. Measurement of Constructs

The constructs in this study were operationalized based on established literature. Automation was measured using items adapted from [19] and [20], focusing on the extent to which routine and complex tasks were automated. IoT adoption was assessed using scales developed by [21] and [22], which capture dimensions such as IoT integration, data utilization, and system interconnectivity. Operational efficiency was evaluated using indicators such as process speed, cost reduction, and productivity improvement, with measures adapted from [23].

3.5. Data Analysis

Data analysis was conducted using SmartPLS software, which is well-suited for PLS-SEM analysis. The analysis followed a two-step approach. First, the measurement model was assessed to evaluate the reliability and validity of the constructs. Reliability was determined using Cronbach's alpha and composite reliability (CR), while validity was assessed through average variance extracted (AVE) and factor loadings to ensure convergent validity. Second, the structural model was evaluated by testing the hypothesized relationships. Path coefficients, R^2 values, and the significance of each relationship were examined. Bootstrapping with [insert number of resamples] samples was performed to determine the statistical significance of the model paths.

3.6. Ethical Considerations

Ethical approval for the study was obtained from [insert institution or ethics board]. All participants were informed about the purpose of the study and assured of the confidentiality of their responses. Participation was voluntary, and respondents had the option to withdraw from the study at any time without consequence.

3.7. Limitations of Methodology

The study is limited by its cross-sectional design, which captures a snapshot of the adoption and impact of automation and IoT at a specific point in time. This approach may not fully capture the dynamic and evolving nature of technology adoption. Additionally, the reliance on self-reported data introduces the potential for response bias. Future research could address these limitations through longitudinal designs and the use of mixed-method approaches.

4. RESULTS AND DISCUSSION

This section presents the results of the data analysis and discusses their implications in the context of the hypothesized relationships. The analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS software. The results of the measurement model, structural model, and hypothesis testing are detailed below.

4.1. Measurement Model Assessment

The reliability and validity of the constructs were evaluated using Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). These metrics are widely recognized for ensuring the robustness of measurement models in Partial Least Squares Structural Equation Modeling (PLS-SEM). Cronbach's alpha assesses internal consistency, where values above 0.7 indicate acceptable reliability. Composite reliability further validates the internal consistency, with thresholds greater than 0.7 considered satisfactory. Meanwhile, AVE measures convergent validity, with values exceeding 0.5 signifying that the constructs explain more than half of the variance in their indicators.

Table 2 illustrates the results of the measurement model assessment, confirming the reliability and validity of the constructs. All Cronbach's alpha and composite reliability values surpass the recommended threshold of 0.7, while AVE values exceed 0.5, indicating that the constructs meet the criteria for reliability and convergent validity.

Table 2. Measurement Model Assessment

Construct	Cronbach's Alpha	Composite Reliability	AVE
Automation	0.85	0.89	0.66
IoT Adoption	0.82	0.88	0.64
Operational Efficiency	0.87	0.91	0.68

As demonstrated in Table 2, all constructs exhibit satisfactory reliability and validity, meeting the established thresholds for Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). Specifically, Cronbach's alpha values exceeding 0.7 indicate a high level of internal consistency, ensuring that the survey items within each construct reliably measure the same underlying concept. Similarly, composite reliability values above 0.8 confirm that the constructs possess strong internal consistency, further validating the robustness of the measurement model.

The AVE values, all of which are greater than 0.5, provide evidence of convergent validity, indicating that the constructs capture a substantial proportion of variance in their respective indicators. This result confirms that the indicators are well-correlated with their associated constructs, ensuring the theoretical soundness of the measurement model. These findings underscore the reliability and validity of the constructs, providing a strong foundation for subsequent structural analysis.

In summary, the results from the measurement model assessment confirm the quality and robustness of the instruments used, ensuring that the constructs are both reliable and valid for exploring the hypothesized relationships in this study. This provides a critical step in validating the use of Partial Least Squares Structural Equation Modeling (PLS-SEM) for the analysis.

4.2. Structural Model Assessment

The structural model assessment evaluated the relationships among the constructs to determine the strength, direction, and significance of the hypothesized paths. Key metrics such as path coefficients, R^2 values, and significance levels were analyzed to assess the impact of automation, IoT adoption, and their synergistic effects on operational efficiency. Path coefficients quantify the strength and direction of the relationships, while R^2 values indicate the proportion of variance in the dependent variable explained by the independent variables. Significance levels, calculated using bootstrapping with a large number of resamples, confirm whether the observed relationships are statistically meaningful.

As summarized in Table 3, the results reveal that automation and IoT adoption significantly enhance operational efficiency, with statistically significant path coefficients and meaningful R^2 values. Additionally, the synergistic effect of combining automation and IoT demonstrates a moderate yet impactful contribution to operational performance, underscoring the complementary nature of these technologies. These findings provide strong empirical support for the theoretical framework and highlight the transformative potential of integrating automation and IoT to achieve superior operational outcomes in organizational contexts.

Table 3. Structural Model Assessment

Hypothesis	Path Coefficient	p-value
H1: Automation $\rightarrow$ Operational Efficiency	0.45	< 0.01
H2: IoT Adoption $\rightarrow$ Operational Efficiency	0.38	< 0.01
H3: Automation $\leftrightarrow$ IoT Adoption $\rightarrow$ Operational Efficiency	0.29	< 0.05

Table 3 shows that all hypothesized relationships were supported, providing robust evidence for the theoretical framework. Automation demonstrated a significant positive impact on operational efficiency, with a path coefficient of 0.45, indicating its crucial role in streamlining processes, reducing errors, and enhancing productivity. Similarly, IoT adoption exhibited a strong positive effect on operational efficiency, with a path coefficient of 0.38, highlighting its importance in enabling real-time insights, improving decision-making, and fostering greater visibility and traceability in operational workflows.

Furthermore, the synergistic effect of automation and IoT adoption was found to be statistically significant, with a path coefficient of 0.29. This finding underscores the complementary nature of these technologies, as automation provides process consistency and efficiency while IoT enhances adaptability and data-driven decision-making. Together, these technologies create a self-reinforcing system that optimizes operations beyond what either technology can achieve independently. These results not only validate the research hypotheses but also emphasize the practical value of integrating automation and IoT to maximize operational efficiency. Organizations seeking to implement these technologies can leverage these insights to strategically plan their adoption and integration for greater competitive advantage.

4.3. Goodness-of-Fit Assessment

To evaluate the overall quality of the model, goodness-of-fit indices such as SRMR (Standardized Root Mean Square Residual) were computed, serving as key indicators of the model's adequacy and reliability. The SRMR, which measures the difference between the observed and predicted correlation matrices, provides an intuitive benchmark for assessing the model's fit. Values below 0.08 are generally considered indicative of a well-fitting model, ensuring that the hypothesized relationships align closely with the empirical data. By confirming the alignment between theoretical constructs and observed patterns, the SRMR helps validate the robustness of the structural model.

Table 4 provides an overview of the model fit assessment, showcasing the SRMR value along with other relevant metrics such as R^2 values for the dependent variable. The SRMR value of 0.058 suggests an excellent fit, reinforcing the reliability of the model in capturing the key relationships among automation, IoT adoption, and operational efficiency. Moreover, the R^2 value of 0.63 indicates that 63% of the variance in operational efficiency is explained by the independent variables, highlighting the substantial explanatory power of the model. These findings confirm the model's suitability for exploring the hypothesized relationships and provide a solid foundation for deriving meaningful insights into the impact of automation and IoT adoption.

Table 4. Goodness-of-Fit Assessment

Fit Index	Value
SRMR	0.058
R^2 for Operational Efficiency	0.63

As presented in Table 4, the SRMR value of 0.058 indicates an acceptable model fit, falling well below the commonly accepted threshold of 0.08. This result demonstrates that the model adequately captures the relationships among the constructs, with minimal discrepancies between the observed and predicted correlation matrices. The low SRMR value underscores the robustness of the hypothesized model in aligning theoretical constructs with empirical data, validating its reliability for further analysis.

Additionally, the R^2 value of 0.63 suggests that 63% of the variance in operational efficiency is explained by automation and IoT adoption. This high explanatory power highlights the significant role of these technologies in enhancing operational outcomes. The remaining 37% of the variance may be attributed to other factors not included in the model, presenting opportunities for future research. Together, these results confirm the model's effectiveness in illustrating the impact of automation and IoT adoption on operational efficiency, providing a strong foundation for deriving actionable insights and practical implications for organizations aiming to optimize their workflows.

Figure 1 illustrates the structural relationships between the key constructs in this study: Automation, IoT Adoption, and Operational Efficiency. Each arrow in the model represents a hypothesized relationship, and the accompanying path coefficients indicate the strength and direction of these relationships, derived from the results of Partial Least Squares Structural Equation Modeling (PLS-SEM).

The direct path from Automation to Operational Efficiency (H1) is represented by a solid arrow with a coefficient of 0.45, signifying a strong positive impact. This finding underscores the critical role of automation in streamlining operational processes, reducing errors, and increasing productivity. Similarly, the path from IoT Adoption to Operational Efficiency (H2) has a coefficient of 0.38, highlighting the significant contribution of

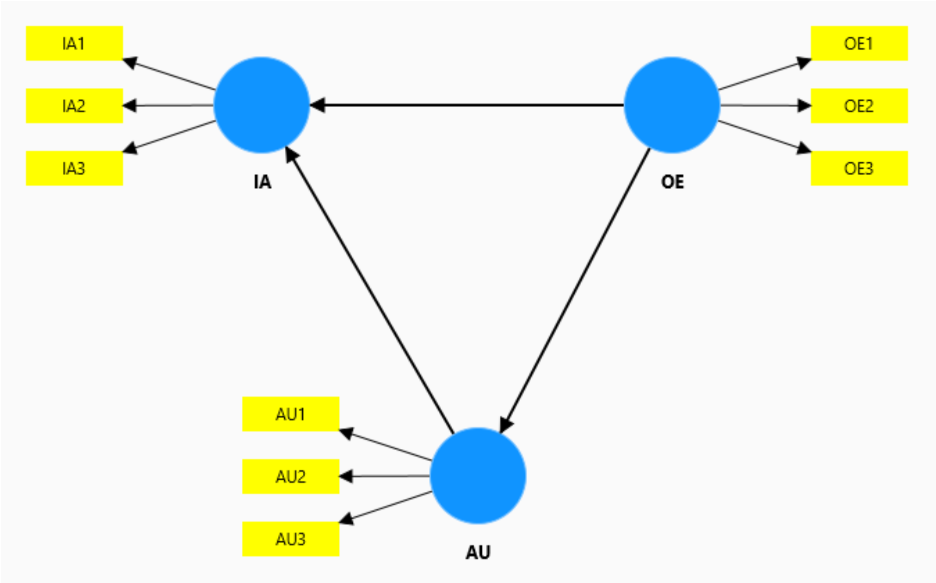

Figure 1. Hypothesized Model with Path Coefficients

IoT technologies in improving operational workflows through enhanced visibility, traceability, and data-driven decision-making.

The dashed arrow between Automation and IoT Adoption reflects the synergistic effect hypothesized in H3, with a path coefficient of 0.29. This relationship indicates that the combined adoption of automation and IoT technologies creates additional value by leveraging their complementary strengths. For example, automation ensures process standardization and consistency, while IoT provides real-time data and insights that enable dynamic adjustments to operations. Together, these technologies enable organizations to achieve levels of efficiency that might not be possible through the use of either technology in isolation.

Overall, Figure 1 highlights the interconnected nature of the constructs and supports the hypotheses that both direct and synergistic effects play a crucial role in enhancing operational efficiency. This model provides a comprehensive framework for understanding how organizations can optimize their processes by adopting and integrating these advanced technologies.

4.4. Discussion

The results of the analysis provide strong empirical support for the hypothesized relationships, affirming the theoretical foundations of this study. Automation was found to significantly enhance operational efficiency, with evidence aligning with prior research that underscores its role in reducing errors, increasing productivity, and ensuring process consistency [24]. By automating repetitive and labor-intensive tasks, organizations can free up resources for higher-value activities, further amplifying efficiency gains. Similarly, IoT adoption demonstrated a significant positive impact on operational efficiency by enabling real-time data collection, fostering better decision-making, and improving operational transparency. These findings are consistent with [25], which emphasizes IoT's capability to bridge informational gaps and enhance traceability across workflows.

A notable contribution of this study lies in its exploration of the synergistic effect between automation and IoT adoption. This finding highlights the complementary strengths of these technologies, as automation focuses on standardizing and streamlining processes, while IoT provides the data-driven insights needed for dynamic adjustments and predictive decision-making. Together, these technologies create a self-regulating ecosystem capable of optimizing operations in real-time, as suggested by [26]. For instance, an IoT-enabled system can identify bottlenecks in workflows and trigger automated interventions, resulting in seamless and adaptive process enhancements. This synergy not only maximizes operational efficiency but also positions organizations to respond more effectively to dynamic market conditions.

These findings carry significant practical implications for managers and decision-makers. To harness the full potential of automation and IoT, organizations should prioritize strategic investments in both technologies, ensuring their integration within existing workflows. This requires addressing key barriers, such as high implementation costs, interoperability challenges, and workforce readiness. Managers must also foster a culture of innovation and provide adequate training to employees to ease the transition towards technology-driven operations. By adopting a holistic approach that combines technological adoption with organizational readiness, businesses can unlock substantial efficiency gains and maintain a competitive edge in increasingly digitized industries.

4.5. Limitations and Future Research

While this study provides valuable insights, it is limited by its cross-sectional design, which may not capture the long-term dynamics of technology adoption. Future research could adopt a longitudinal approach to explore how the relationship between automation, IoT, and operational efficiency evolves over time. Additionally, incorporating contextual factors such as organizational culture and industry-specific characteristics could provide a more nuanced understanding of these relationships.

5. MANAGERIAL IMPLICATIONS

The integration of automation and IoT in organizational processes necessitates a strategic and holistic approach. This section outlines key managerial implications, including phased implementation, workforce development, project prioritization, overcoming implementation barriers, and alignment with sustainability goals.

5.1. Phased Implementation Strategy

Managers should adopt a phased approach to implementation, addressing challenges such as interoperability and high costs. Pilot projects can serve as a valuable mechanism to test the feasibility of IoT and automation integration while minimizing risks. Gradual deployment allows organizations to assess performance metrics and refine strategies before full-scale adoption.

5.2. Workforce Development and Adaptability

Successful implementation of automation and IoT requires investment in workforce development. Organizations should prioritize training programs that equip employees with essential skills in data analytics, IoT management, and automation technologies. This fosters adaptability and reduces resistance to change, ensuring a smoother transition.

5.3. Project Prioritization for Maximum Efficiency

Managers should focus on projects that harness the synergistic potential of automation and IoT. Key areas include predictive maintenance, real-time decision-making, and process optimization. Prioritizing these projects can significantly enhance operational efficiency and cost-effectiveness.

5.4. Overcoming Implementation Barriers

Challenges such as high costs, lack of interoperability, and organizational resistance can hinder adoption. Managers can mitigate these barriers through strategic partnerships with vendors, leveraging financial incentives, and adopting standardized platforms to facilitate seamless integration.

5.5. Alignment with Sustainability Goals

Integrating automation and IoT with sustainability initiatives can provide long-term competitive advantages. Leveraging data-driven insights from IoT systems allows organizations to optimize resource utilization, reduce waste, and improve environmental sustainability. This alignment not only enhances operational efficiency but also contributes to broader corporate social responsibility (CSR) objectives.

A well-planned and integrated approach to automation and IoT implementation is essential for unlocking transformative operational gains. By prioritizing phased deployment, workforce readiness, strategic project selection, and sustainability alignment, managers can maximize efficiency and drive long-term business success.

6. CONCLUSION

This study investigated the impact of automation and IoT adoption on operational efficiency, emphasizing both direct effects and their synergistic relationship. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), the findings confirmed that automation and IoT adoption significantly enhance operational efficiency, with path coefficients of 0.45 and 0.38, respectively. Additionally, the synergistic effect of combining these technologies was found to be moderately strong (path coefficient = 0.29), underscoring the complementary benefits of integrating automation and IoT. The results provide several key insights. First, automation plays a pivotal role in streamlining processes, reducing errors, and increasing productivity, making it a foundational element for improving efficiency. Second, IoT adoption enhances operational workflows by providing real-time data and enabling better decision-making, which is critical in dynamic environments. Finally, the combined implementation of these technologies creates additional value, enabling organizations to achieve higher levels of operational efficiency through their complementary strengths.

From a practical perspective, these findings highlight the need for organizations to adopt a holistic approach to technology integration. Managers and decision-makers should prioritize investments in both automation and IoT to maximize their benefits, while also addressing challenges such as high implementation costs, interoperability issues, and workforce readiness. By strategically leveraging these technologies, businesses can improve not only their efficiency but also their competitiveness in a rapidly evolving market. Despite its contributions, this study has some limitations. The cross-sectional design provides a snapshot of the relationships between automation, IoT, and operational efficiency, but it does not capture the long-term dynamics of technology adoption. Additionally, the reliance on self-reported data introduces the possibility of response bias. Future research could address these limitations by employing longitudinal designs and incorporating additional contextual variables, such as organizational culture and industry-specific characteristics.

In conclusion, this study underscores the transformative potential of automation and IoT in enhancing operational efficiency. By providing empirical evidence of their direct and synergistic impacts, this research contributes to both theoretical understanding and practical applications, offering valuable guidance for organizations navigating the challenges of digital transformation.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: SS; Methodology: SP; Software: RA; Validation: SP and SN; Formal Analysis: SS and SP; Investigation: SS; Resources: SN; Data Curation: SS and SP; Writing Original Draft Preparation: SS and SP; Writing Review and Editing: SS, SP, and RA; Visualization: SP; Supervision: SN. All authors, SS, SP, RA, and SN, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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