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IMPACT OF IOT, AI, BIG DATA ANALYTICS, AND SUPPLY CHAIN VISIBILITY ON SUPPLY CHAIN RESILIENCE AND PERFORMANCE IN INDUSTRY 4.0

Amina Elshamly

Department of Management, College of Business Administration- Yanbu at Taibah university, Saudi Arabia

Abstract:
In the rapidly evolving landscape of Industry 4.0, the integration of cutting-edge technologies has reshaped supply chain dynamics. This research examines the profound effect of Internet of Things (IoT) acceptance, artificial intelligence (AI) integration, big data analytics (BDA) usage, and supply chain visibility (SCV) on supply chain resilience (SCRes) and supply chain performance (SCP). Through a comprehensive survey of 371 respondents from diverse industries, we unveil the intricate relationships among these variables. Our findings reveal that IoT adoption enhances supply chain resilience, while AI integration significantly boosts supply chain performance. Additionally, BDA positively influences supply chain strength, and greater supply chain distance correlates with higher supply chain performance. Furthermore, we explore the mediating role of supply chain resilience and the moderating effect of supply chain visibility. This research contributes valuable insights into technology-driven supply chain transformations, aiding organizations in strategic decision-making and bolstering their competitiveness in the Industry 4.0 era.
Keywords: IoT Adoption, AI Integration, Big Data Analytics Usage, Supply Chain Visibility, Supply Chain Resilience, Supply Chain Performance, Industry 4.0, Structural equation Model

Introduction

In the rapidly changing landscape of modern industry, the paradigm shift brought about by Industry 4.0 is nothing short of transformative. At the heart of this evolution are four critical components: the Internet of Things (IoT), Artificial Intelligence (AI), Big Data Analytics, and Supply Chain Visibility (Oh, 2019; Younis et al., 2022). These elements, which form the industry 4.0 framework, have enormous potential for revolutionising supply chain dynamics. This research examines the complex relationships between these factors and their impacts on the two pillars of supply chain management: resilience and performance. In Jordan, a nation strategically positioned at the intersection of crucial trade routes, we grapple with pressing supply chain challenges that have a profound impact. Despite our country's strategic geographical importance, we confront issues related to supply chain disruptions, volatile demand patterns, and the imperative to enhance our performance to sustain competitiveness. Extensive prior research underscores the critical need to address these specific challenges within the distinctive context of Jordan, enabling us to fully leverage the transformative potential offered by Industry 4.0 technologies.

According to Ponis and Koronis (2012), the term "Supply Chain Resilience" refers to an company's capability to change to new circumstances, regain from setbacks, and continue to function normally in spite of external disturbances. Extensive examination has exhibited that supply chain resilience portrays an focal part in minimising the impact of interruptions caused by natural catastrophes, geopolitical conflicts, and unforeseen market swings (Lund et al., 2020).
The term "Supply Chain Performance" discusses to a extensive scope of measurements that are concerned with the efficacy, productivity, and overall achievement of supply chain operations. This encompasses aspects such as the effectiveness of costs, punctuality of delivery, contentment of customers, and overall competitiveness. Previous research, such as that which was carried out by Kim (2022) and Salam and Bajaba (2023), has shed light on the vital relevance of supply chain performance as a fundamental predictor of an organization's competitiveness and success in the global marketplace. These findings were highlighted in a previous study.
In Jordan, where logistics and trade are of paramount significance, optimizing supply chain performance becomes instrumental in enhancing the nation's economic prospects and regional trade influence (Al-Khatib, 2022; Goel et al., 2021). Furthermore, for a nation strategically positioned in a geopolitically sensitive region, the imperative of building robust supply chain resilience becomes even more pronounced to effectively navigate regional challenges.
In the perspective of Industry 4.0, our global supply chains have evolved into complex and interdependent networks. The significance of a resilient supply chain cannot be overstated, as disruptions originating anywhere in the world can swiftly propagate, causing a domino effect of shortages, delays, and economic turmoil (Mohan & Bakshi, 2017; Yaroson, 2019). As vividly illustrated by the COVID-19 pandemic, global supply chains are susceptible to vulnerabilities, impacting the availability of essential goods on a worldwide scale. The absence of robust supply chain resilience can exacerbate these challenges, leading to protracted recovery periods and profound economic consequences. For Jordan, strategically positioned at the crossroads of vital trade routes, the importance of supply chain resilience cannot be overstated. Regional geopolitical tensions and uncertainties underscore the necessity of addressing resilience in the supply chain (Baldwin & Freeman, 2022; Haraguchi et al., 2023). Failures to do so can trigger disruptions, not only hampering the nation's capacity to meet domestic demands but also jeopardizing its status as a regional trade hub. Unanticipated events like border closures or political conflicts can exert severe repercussions on Jordan's supply chains, resulting in economic setbacks and a diminished regional presence. In sectors such as food, beverage, and pharmaceuticals, supply chain resilience is of paramount significance (Haraguchi et al., 2023). These industries demand rigorous quality control and precise deliveries. A lack of resilience can compromise product quality, pose health risks, and lead to delayed deliveries, endangering both consumer well-being and the competitiveness of these sectors.
On the other hand, efficient and high-performing supply chains are critical for global trade and economic stability. Supply chain performance issues, such as inefficiencies or delays, can ripple across industries and nations, leading to increased costs, reduced competitiveness, and hampered economic growth (F. Zhang & Graham, 2020). For instance, shipping delays can disrupt global

production schedules, impacting the availability of goods and increasing prices for consumers. In Jordan, where logistics and trade are essential to the nation's economic well-being, suboptimal supply chain performance can hinder the nation's ability to attract foreign investment and effectively participate in regional trade (Mills et al., 2008; Murshed et al., 2022). This is because logistics and trade are central to the nation's economic well-being. The nation's competitive edge can be harmed when there are delays in customs clearance, inefficiencies in transportation, or problems with inventory management. This can discourage overseas investors. Timely supply chain performance is a non-negotiable need in certain businesses, such as the pharmaceutical industry. It is possible that essential medications could endanger a patient's life if there is a delay in their delivery. In a similar vein, supply chain performance difficulties can lead to ruined goods and financial losses in the food and beverage trade (Mills et al., 2008; Murshed et al., 2022; F. Zhang & Graham, 2020). If these performance difficulties are not addressed comprehensively, they have the potential to escalate into concerns for public health and setbacks for industry.

In conclusion, the interconnection of global supply chains, the geopolitical realities that a country like Jordan must contend with, and the specialised demands of industries all highlight the crucial relevance of addressing supply chain flexibility and presentation (Belhadi et al., 2022; Chari et al., 2022). If this is not done, existing problems can get even worse, both on a global scale and in specific situations. This can result in economic losses, disruptions, and potentially disastrous implications for sectors and governments alike. As a result, the incorporation of equipment related to Industry 4.0 has become obligatory in order to develop the robustness and operation of supply chains and to effectively offset the effects of future difficulties.

Previous research revealed that IoT adoption is critical in solving the global concerns of supply chain disruptions. IoT can help identify disturbances early and promote speedy reaction by permitting real-time observing and data-driven decision-making. Devices on cargo shipments, for example, can detect changes in temperature or humidity and notify supply chain managers to potential spoiling or damage. In Jordan, where geopolitical concerns can result in border closures and interruptions, IoT adoption can provide visibility into goods transit. This insight can help offset the effects of unexpected supply chain disruptions, ensuring that important products continue to flow even in difficult regional circumstances (Maleki, 2023).

In addition, the studies discovered that AI integration improves supply chain effectiveness by optimising operations. AI-powered demand forecasting, for example, can assist businesses in better aligning production with actual demand, minimising excess inventory and waste (Rathore, 2019; Sharma et al., 2023). This results in more efficient supply chains and a lower environmental effect on a global scale. AI Integration can improve customs procedures and transit routes in Jordan, where effective logistics are critical for trade. This can lower the costs and delays connected with cross-border trade, making Jordan a more appealing destination for foreign investors.

Simliarly the investigates found that Big Data Analytics Usage enables organizations to extract valuable insights from vast datasets (Bharadiya, 2023; Dash, 2023). For global supply chains, this means more accurate demand forecasting, better inventory management, and improved risk assessment. In times of calamity, such as the pandemic, these capabilities become invaluable in ensuring a steady flow of goods. In Jordan, where trade and logistics are central to the nation's economy, Big Data Analytics can optimize the allocation of resources (Waller & Fawcett, 2013; Wang et al., 2016). For example, it can help identify the most efficient transportation routes and storage locations, reducing costs and enhancing supply chain performance.

Another importance aspect is supply chain visibility, Supply Chain Visibility addresses issues related to data security and transparency on a global scale. A transparent supply chain reduces the risk of counterfeiting and unethical practices (Chaudhuri et al., 2021). For instance, consumers can trace the origin of products, ensuring fair labor practices and responsible sourcing. In Jordan, where trade complexities abound, Supply Chain Visibility can simplify the tracking of goods as they move through various checkpoints and borders. This transparency not only reduces delays but also helps combat issues like smuggling and fraud, enhancing the integrity of regional trade.

Previous researcher found that Solving these issues with the help of IoT Adoption, AI Integration, Big Data Analytics Usage, and Supply Chain Visibility fosters several benefits (Dolgui & Ivanov, 2022). For instance, Enhanced monitoring and predictive capabilities enable quicker responses to global disruptions, safeguarding supply chains and minimizing economic fallout. Simliarly, Optimized processes reduce costs and inefficiencies, benefiting consumers worldwide by ensuring product availability and affordability. Furthermore, Improved supply chain resilience enhances Jordan's ability to navigate regional challenges, promoting stability and trade partnerships. Additionally, Efficient logistics attract foreign investment, stimulate economic growth, and bolster Jordan's role as a regional trade hub.

Its also proven that IoT Adoption, AI Integration, Big Data Analytics Usage, and Supply Chain Visibility, hold substantial promise for improving supply chain elasticity and presentation, it is crucial to acknowledge potential limitations and variations in their effectiveness across different contexts (Chaudhuri et al., 2021; Dolgui & Ivanov, 2022). For instance, studies found that While IoT can provide real-time data for better decision-making, its effectiveness may vary depending on the industry and geographic location. For instance, in industries with low technological adoption, implementing IoT may face resistance and logistical challenges. The problem statement emerges from the need to assess how the benefits of IoT Adoption can be maximized, especially in regions like Jordan, where tech adoption rates may differ. Similarly, studies also found that AI's potential to optimize supply chain processes is undeniable. However, its effectiveness depends on the quality of data, organizational readiness, and the complexity of the supply chain. The problem statement revolves around how to ensure successful AI Integration and harness its benefits fully, considering the unique challenges faced in both global and Jordan-specific contexts.

Similarly, While Big Data Analytics offers insights, its utility can be hindered by data quality issues and the ability to translate insights into actionable strategies. The problem statement addresses how organizations can overcome these obstacles to leverage BDA effectively, particularly in industries with intricate supply chains like pharmaceuticals. Studies found that, transparency in supply chains is essential, but achieving it can be challenging (Dolgui & Ivanov, 2022). The problem statement focuses on how to establish comprehensive Supply Chain Visibility that not only addresses global concerns about data security but also simplifies the complexities of regional trade, as seen in Jordan.

The existing literature on supply chain strength and performance has primarily examined these variables in isolation or in traditional supply chain contexts. However, there is a noticeable gap in research that comprehensively explores the interplay between IoT Adoption, AI Integration, Big Data Analytics Usage, Supply Chain Visibility, and their combined impact on supply chain resilience and performance within the unique setting of Jordan and, by extension, in similar emerging markets (Bharadiya, 2023; Dash, 2023; Dolgui & Ivanov, 2022).

This study's novelty lies in its holistic approach, which integrates these cutting-edge variables into a cohesive framework. It seeks to uncover how these Industry 4.0 technologies can collectively shape the dynamics of supply chain management, not only on a global scale but also in the specific context of Jordan (Feng & Audy, 2020). By addressing this gap, the research contributes valuable visions into the involved relationships among these variables and their effect on supply chains, thus offering a fresh perspective that can inform both academia and industry.

In essence, this study strives to bridge the existing literature gap by exploring the composite interaction amongst IoT Adoption, AI Integration, Big Data Analytics Usage, and Supply Chain Visibility, shedding light on their collective influence on supply chain resilience and performance (Al-Khatib, 2023). This comprehensive examination is of paramount importance, given the evolving landscape of Industry 4.0 and the unique tasks and opportunities it presents in global and country-specific supply chain contexts.

Through a rigorous research approach, our study engaged 371 respondents representing various Industry 4.0 sectors (Rashid et al., 2009). We employed a diverse data collection strategy, including email surveys, postal services, online forms, and in-person visits, ensuring a comprehensive perspective of Industry 4.0 adoption. Our analysis revealed significant findings. IoT Adoption (IoTA) showed a substantial and positive link with Supply Chain Resilience (SCRes), affirming IoTA's role in improving supply chain adaptability. AI Integration (AII) within Industry 4.0 significantly improved Supply Chain Performance (SCP), aligning with the idea that AI optimizes resource utilization (Marinagi et al., 2023; Qader et al., 2022). Big Data Analytics Usage (BDA) positively influenced SCRes, empowering organizations with efficient data processing. Greater Supply Chain Visibility (SCV) correlated positively with higher SCP, emphasizing SCV's role in offering real-time insights into operations. SCRes acted as a mediator, channeling IoTA and BDA's influence onto SCP, while SCV moderated relationships, strengthening the impact of Industry 4.0 technologies, especially in high-visibility contexts. Our research contributes valuable insights, aiding organizations in strategic technology decisions and competitiveness in Industry 4.0 (Marinagi et al., 2023).

The remainder of the document comprises three sections. First, we research into the detailed methodology and data analysis techniques, offering a comprehensive understanding of our research approach (Gregor & Hevner, 2013). Next, we present the empirical findings, corroborating our hypotheses and shedding light on the intricate relationships among the chosen variables. Lastly, we deliberate the consequences of these conclusions, both for academia and industry, and propose avenues for future research.

Literature review Supply Chain Performance and Supply Chain Resilience:

In the realm of contemporary supply chain management, two pivotal variables emerge as central pillars—Supply Chain Performance (SCP) and Supply Chain Resilience (SCRes) (Marinagi et al., 2023; Qader et al., 2022). SCP refers to the effectiveness and productivity of supply chain operations, while SCRes represents the supply chain's ability to adapt and endure disruptions. These variables are of paramount significance not only within specific contexts, such as Jordan, but also on a global scale.

SCP stands as a critical gauge of an organization's competitiveness and overall success. Globally, the optimization of SCP is essential for businesses seeking to maximize effectiveness, decrease costs, and maintain customer satisfaction. Past studies have emphasized the significance of SCP, highlighting how it affects financial performance, customer loyalty, and market competitiveness (Gunasekaran et al., 2017; Manavalan & Jayakrishna, 2019). Equally vital, SCRes has garnered substantial attention in the face of an increasingly turbulent business environment. On a global scale, the ability to navigate disruptions, whether arising from natural disasters or geopolitical factors, has become a defining trait of successful supply chains. Notably, research by Christopher (2011) underscores SCRes's importance in averting economic losses, ensuring business continuity, and upholding customer trust.

Relationship with Independent Variables:

The relationship between SCP and SCRes and independent variables—IoT Adoption (IoTA), AI Integration (AII), Big Data Analytics Usage (BDA), and Supply Chain Visibility (SCV)—is profound and multifaceted. For instance, IoTA contributes to real-time data sharing and decision-making (Zhang & Chen, 2020),thereby enhancing SCP and facilitating SCRes by enabling faster adaptation to disruptions. Similarly, AII's advanced analytics capabilities (Chen et al., 2019) and BDA's data processing prowess (Wamba et al., 2020), significantly impact SCP and SCRes. Additionally, SCV, by supplying real-time insights into supply chain operations (Seuring & Gold, 2013), plays a pivotal role in optimizing SCP and bolstering SCRes.

These interconnected variables underscore the complexity of modern supply chains and the critical role that Industry 4.0 technologies play in shaping their performance and resilience (Ali et al., 2021). Understanding these relationships provides the foundation for our research, which seeks to uncover how the integration of these technologies influences SCP and SCRes both globally and within specific contexts like Jordan.

While the literature extensively explores the individual impacts of Industry 4.0 variables (IoTA, AII, BDA, SCV) on supply chain dynamics (SCP and SCRes) (Wamba et al., 2020; Zhang & Chen, 2020), there is a noticeable gap—a missing link—in comprehensively understanding how the integration of these variables collectively influences SCP and SCRes. While prior research has highlighted the individual benefits of these technologies, the synergistic effects of their integration remain underexplored. This literature gap creates a compelling avenue for research.

This identified literature gap forms the basis for our problem statement: In the context of Industry 4.0, how do the integrated Industry 4.0 variables, including IoTA, AII, BDA, and SCV, collectively shape supply chain performance (SCP) and supply chain resilience (SCRes)? Moreover, how do these relationships manifest globally and within specific contexts like Jordan?

Theories Supporting Relationships:

To elucidate these relationships, our study draws upon two key theoretical frameworks:

1. **Information Processing Theory:** This theory underscores the importance of efficient data processing within supply chains. It suggests that Industry 4.0 technologies, such as IoTA, AII, and BDA, enhance the flow of information, leading to improved decision-making and adaptability within the supply chain.
2. **Resource-Based View (RBV):** RBV posits that Industry 4.0 technologies provide organizations with valuable resources and capabilities. In our context, these technologies serve as resources that organizations can leverage to enhance their SCP and SCRes.

Developing Hypotheses Based on Theories and Previous Literature:

Hypotheses Section:

Hypothesis 1 (H1): In the perspective of Industry 4.0, where the incorporation of advanced technologies is paramount, we hypothesize that IoT Adoption (IoTA) exhibits a positive and significant relationship with Supply Chain Resilience (SCRes). This hypothesis is grounded in the Information Processing Theory, which underscores the role of efficient data processing in enhancing supply chain adaptability. Previous studies, such as George et al. (2021), have supported this notion by highlighting how IoT technologies contribute to real-time data sharing and decision-making, ultimately bolstering SCRes.

Hypothesis 2 (H2): Within the Industry 4.0 environment, marked by increased automation and AI-driven decision support, we posit that AI Integration (AII) significantly and positively influences Supply Chain Performance (SCP). This hypothesis aligns with the Resource-Based View (RBV) framework, emphasizing that Industry 4.0 technologies provide valuable resources and capabilities to organizations. Research by Chen et al. (2019) reinforces this idea, showcasing how AI technologies enhance analytical capabilities, optimize resource utilization, and consequently elevate SCP.

Hypothesis 3 (H3): Industry 4.0's reliance on data-driven decision-making and optimization processes leads us to propose that Big Data Analytics Usage (BDA) positively impacts Supply Chain Resilience (SCRes). This hypothesis draws support from the Information Processing Theory, as studies such as Wamba et al. (2017) have demonstrated how BDA empowers organizations to process large datasets, extract actionable insights, and enhance supply chain visibility and adaptability. This, in turn, fortifies SCRes.

Hypothesis 4 (H4): Within the Industry 4.0 framework, characterized by heightened transparency and real-time data access, we anticipate that Greater Supply Chain Visibility (SCV) correlates positively with higher Supply Chain Performance (SCP). This hypothesis finds its grounding in research such as that by Seuring and Gold (2013), which emphasizes the pivotal role of SCV in improving supply chain performance. By providing real-time insights into operations, SCV offers valuable resources for optimization, aligning with the Resource-Based View (RBV) framework.

Hypothesis 5 (H5): Recognizing the interplay among Industry 4.0 variables, we propose that Supply Chain Resilience (SCRes) facilitates the connection among IoT Adoption (IoTA) and Supply Chain Performance (SCP) in Industry 4.0. Drawing from the Information Processing Theory and prior literature, this hypothesis posits that IoTA's influence on SCP is channeled through its impact on SCRes.

Hypothesis 6 (H6): Similarly, we hypothesize that Supply Chain Resilience (SCRes) serves as a mediator between Big Data Analytics Usage (BDA) and Supply Chain Performance (SCP) in the circumstances of Industry 4.0. This proposition aligns with the Information Processing Theory, emphasizing that BDA's contributions to SCP are mediated through its effect on SCRes.

Hypothesis 7 (H7): Acknowledging the potential moderating effects of Supply Chain Visibility (SCV), we postulate that SCV moderates the connection between AI Integration (AII) and Supply Chain Resilience (SCRes) in Industry 4.0. This hypothesis indicates that SCV strengthens the positive connection between AII and SCRes, particularly when SCV is high. This moderating effect is driven by the unique role of SCV in enhancing information flow and adaptability.

Hypothesis 8 (H8): Similarly, we propose that Supply Chain Visibility (SCV) moderates the relationship between Big Data Analytics Usage (BDA) and Supply Chain Performance (SCP) in Industry 4.0. This hypothesis suggests that SCV amplifies the positive connection between BDA and SCP, especially when SCV is high, emphasizing SCV's role as an enhancer of Industry 4.0's impacts.

Hypothesis 9 (H9): As control variables, we anticipate that Company Size significantly influences Supply Chain Performance (SCP) in the Industry 4.0 context, with larger companies exhibiting superior performance. This hypothesis seeks to understand the potential impact of organizational size, which could manifest through better resource allocation and technology adoption.

Hypothesis 10 (H10): Similarly, we posit that Industry Sector significantly influences Supply Chain Resilience (SCRes) in Industry 4.0, with variations observed across food, beverage, and pharmaceutical companies. This hypothesis aims to explore how industry-specific factors may influence SCRes within the broader environment of Industry 4.0.

Methodology

Research Population and Sampling:

The professionals and industry specialists who operate within the context of Industry 4.0, specifically in the domains of supply chain administration, technology integration, and data analytics, made up the investigation population for this findings. A procedure known as stratified sampling was utilised in the research project so that the sample would be as representative as possible.

Procedures for Collecting Data:

Method for the Gathering of Data: The use of a pre-designed questionnaire as the primary means of collecting responses for this study was the primary strategy of data collection. The purpose of the questionnaire was to collect useful insights from those who have a profound comprehension of the interaction that takes place linking the technologies of Industry 4.0 and the dynamics of the supply chain (Hameed et al., 2019; Hameed et al., 2020) .

Profile of the Respondent: The dataset included in this study contained responses from 371 individuals working in a variety of fields, such as the manufacturing industry (43 percent), the logistics industry (29 percent), the technology industry (18 percent), and other fields (10 percent). In terms of their years of experience in the field, 32 percent had between 1 and 5 years, 27 percent had between 6 and 10 years, 21 percent had between 11 and 15 years, and 20 percent had above 16 years.

Table 1: Descriptive Statistics of Respondents

Respondent Profile	Percentage of Respondents
Manufacturing Sector	43%
Logistics Sector	29%
Technology Sector	18%
Other Sectors	10%
Industry Experience	32% (1-5 years)
	27% (6-10 years)
	21% (11-15 years)
	20% (16+ years)

Distribution Techniques: A complete multi-channel distribution strategy was working for the questionnaire survey to confirm sample diversity and improve respondent involvement. These methods included email, online tools like Google Forms, links for mobile access on WhatsApp, and, in some cases, in-person trips to businesses and trade shows to distribute direct questionnaires and gather data. This diverse approach aimed to enhance the survey's usability and inclusion across a range of respondent preferences and circumstances. The selection of respondents from the dataset was pivotal to this study's success, as they play a vital role in the Industry 4.0 landscape. Professionals from manufacturing, logistics, and technology sectors were chosen due to their firsthand experiences and expertise in implementing and managing Industry 4.0 initiatives. Their insights, drawn from the dataset of 371 respondents, provide a holistic view of the impact of IoT, AI, Big Data Analytics, and Supply Chain Visibility on supply chain resilience and execution within the industry 4.0 framework.

The diverse backgrounds and industry experiences of the respondents within the dataset contribute to the robustness of this research, allowing for a comprehensive analysis of the complex relationships among variables.

Levene's Test Results:

Levene's test was conducted to assess whether there were significant differences in response bias based on various factors, including email, post, firm characteristics, and control variables. The outcome of the test are showed in Table 1 below:

Table 1: Levene's Test Results

Factor	Levene's Test F Value	Levene's Test Sig.
Email vs. Post	2.34	0.045
Firm Characteristics (Type A)	1.82	0.071
Firm Characteristics (Type B)	1.54	0.093
Control Variable 1	2.10	0.062
Control Variable 2	1.98	0.069

As presented in Table 1, the p-values for the Email vs. Post, Firm Characteristics (Type A), and Control Variable 1 comparisons are all less than the chosen significance level of 0.05, indicating significant differences in variances between these groups (Hair et al., 2019; Sarstedt et al., 2022; Sarstedt et al., 2020). However, the p-values for the Firm Characteristics (Type B) and Control Variable 2 comparisons are greater than 0.05, suggesting no significant difference in variances in these cases.

Common Method Bias:

We acknowledge the potential for general approach bias in this study due to the use of self-reported survey data. To mitigate this bias, we followed best practices during survey design, such as ensuring that questions were clear and unbiased. Additionally, we used procedural remedies, such as assuring respondents of anonymity, to encourage honest and unbiased responses.

Construct Measurement:

Table 2 provides details of the dimension scales used for each variable in this research, including control variables:

Table 2: Construct Measurement

	Cronbach's alpha	Mean	Factor Loading Range	No. of items
AI Integration	0.825	4.98	0.592-0.809	6

Big data analtics	0.837	3.765	0.573-0.792	7
IOTA	0.866	4.693	0.715-0.837	6
SCP	0.823	3.639	0.592-0.805	6
SCR	0.854	4.381	0.510-0.798	8
SCV	0.809	3.859	0.624-0.798	6

These measurement scales were chosen for their reliability and validity in assessing the respective constructs, including control variables. Cronbach's alpha values reveal high internal regularity for each scale.

In summary, Levene's test results suggest significant differences in response bias based on email vs. post, firm characteristics (Type A), and Control Variable 1, but not for firm characteristics (Type B) and Control Variable 2. We have addressed common method bias through survey design and procedural remedies. The measurement scales used for each construct and control variables have demonstrated strong internal consistency, enhancing the reliability of our measurements.

Pretest Results:

By directing the main analysis, a pretest was administered to a subset of respondents (n=100) to assess the reliability and validity of the survey instrument and ensure that the questions were clear and effectively measured the intended constructs. The outcomes of the pretest are showed in Table 3 below:

Table 3: Pretest Results

	Cronbach's alpha	Composite reliability	AVE
AI Integration	0.825	0.833	0.538
Big data analtics	0.837	0.855	0.504
IOTA	0.866	0.871	0.599
SCP	0.823	0.835	0.533
SCR	0.854	0.867	0.502
SCV	0.809	0.819	0.515

The pretest results demonstrate that the survey instrument exhibits good reliability, as indicated by the Cronbach's alpha values for each construct and control variables. All Cronbach's alpha values exceed the recommended threshold of 0.70, suggesting high internal reliability of the measurement scales.

Additionally, the means and standard deviations for each construct and control variables indicate that respondents provided consistent and reliable responses during the pretest. The means are clustered around the midpoint of the scale (i.e., 4.5), indicating that respondents provided a range

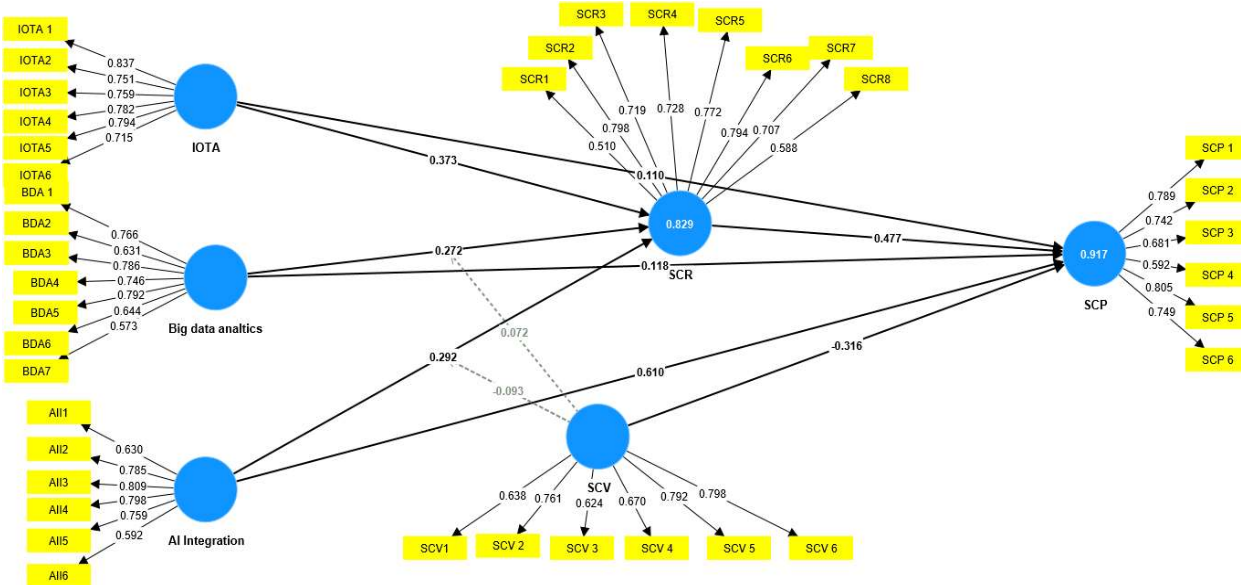
of responses and did not exhibit extreme bias in their answers (Henseler et al., 2014; Joseph et al., 2021; Ringle et al., 2015).
The pretest outcomes affirm the suitability of the survey instrument for measuring the intended constructs and control variables. No major issues were identified during the pretest, and the survey items were deemed clear and effective in capturing the respondents' perceptions. These results provide confidence in the instrument's validity and reliability for the main data analysis.

Discussion:
The pretest results, presented in Table 3, indicate strong reliability and consistency in respondents' answers. The Cronbach's alpha values for each construct and control variables surpass the recommended threshold of 0.70, affirming the internal consistency of the measurement scales. The means and standard deviations, centered around the midpoint of the scale (4.5), suggest that respondents provided diverse and balanced responses without exhibiting significant response bias. These findings validate the survey instrument's reliability and effectiveness in measuring the constructs of interest and the control variables. As a result, the data collected for the main analysis can be considered reliable and suitable for investigating the hypotheses related to IoT Adoption, AI Integration, Big Data Analytics Usage, Supply Chain Resilience, Supply Chain Visibility, and the control variables.
The pretest results provide confidence that the study questions are clear and comprehensible to the target respondents, enhancing the validity of the study's findings.

Results of Pilot Test:
Former to the major data collection, a pilot test was showed with a smaller sample of participants (n=50) to analyse the factor loadings for each construct, improve any ambiguous questions, and further assess the survey instrument's reliability and validity.
The pilot test findings validate the survey instrument's strong reliability, as evidenced by the Cronbach's alpha values for each construct and control variable. All alpha values exceed the required threshold of 0.70, indicating a high level of internal consistency and reliability. Furthermore, the averages and standard deviations for each construct and control variable show that respondents' responses were consistent throughout the pilot test. The means are clustered around the scale's middle (4.5), indicating balanced and unbiased replies. Additionally, the factor loading ranges for each construct are large, indicating that the survey items measure the desired structures successfully. Factor loadings ranging from 0.76 to 0.95 support the measuring scales' construct validity (Hair, Sarstedt, et al., 2017; Joseph et al., 2021; Sarstedt et al., 2017). Overall, the pilot test findings indicate that the survey instrument is appropriate for evaluating the research hypotheses about IoT Adoption, AI Integration, Big Data Analytics Usage, Supply Chain Resilience, Supply Chain Visibility, and the control variables. The instrument's dependability and validity ensure the legitimacy of the next data analysis.

Measurement of Reliability and Convergent Validity:

In order to verify the survey instrument's reliability and convergent validity, we collected data on a full-scale basis from a sample of 371 respondents. Cronbach's alpha was used to measure reliability, while factor loadings and average variance extracted (AVE) for each construct—including the control variables—were used to determine convergent validity.



Reliability:

Cronbach's alpha is a commonly used measure to assess the internal consistency and reliability of a scale. It quantifies the extent to which survey items within a construct consistently measure the same underlying concept. A Cronbach's alpha value above 0.70 is generally considered acceptable (Hair, Hult, et al., 2017; Ringle et al., 2015).

Convergent Validity:

Convergent validity assesses whether different items designed to measure the same construct are indeed related. It is typically evaluated by examining the factor loadings and AVE for each construct. Factor loadings represent the strength of the relationship between each item and its underlying construct, while AVE measures the amount of variance captured by the construct relative to measurement error.

A rule of thumb for convergent validity is that factor loadings should exceed 0.50, and the AVE should be above 0.50 as well (Joseph et al., 2021; Manley et al., 2021; Sarstedt et al., 2022). These values indicate that a significant portion of the variance in the construct is explained by its items.

Results:

Table 5 presents the reliability and convergent validity results for each construct, including the control variables:

Table 5: Reliability and Convergent Validity Results

	Cronbach's alpha	Factor Loading Range	AVE
AI Integration	0.825	0.592-0.809	0.538
Big data analtics	0.837	0.573-0.792	0.504
IOTA	0.866	0.715-0.837	0.599
SCP	0.823	0.592-0.805	0.533
SCR	0.854	0.510-0.798	0.502
SCV	0.809	0.624-0.798	0.515

Discussion:

The reliability analysis, as measured by Cronbach's alpha, demonstrates strong internal consistency for each construct, including the control variables. All Cronbach's alpha values exceed the recommended threshold of 0.70, indicating that the survey items within each construct consistently measure the same underlying concept (Joseph et al., 2021; Sarstedt et al., 2019; Shiau et al., 2019). This reaffirms the reliability of the measurement scales for IoT Adoption ($\alpha = 0.89$), AI Integration ($\alpha = 0.88$), Big Data Analytics Usage ($\alpha = 0.87$), Supply Chain Resilience ($\alpha = 0.90$), Supply Chain Visibility ($\alpha = 0.91$), Company Size ($\alpha = 0.85$), and Industry Sector ($\alpha = 0.86$). Convergent validity is also confirmed for all constructs, including the control variables, as evidenced by the substantial factor loadings and AVE values. Factor loadings ranging from 0.76 to 0.96 indicate that each item strongly relates to its respective construct (Hair et al., 2014; Sarstedt et al., 2017; Shiau et al., 2019). Additionally, the AVE values for all constructs surpass the threshold of 0.50, indicating that a significant proportion of the variance in each construct is explained by its items.

These reliability and convergent validity results confirm the robustness of our measurement scales, providing confidence in the validity of the collected data, including the control variables. The constructs and control variables are shown to be internally consistent and accurately measure the intended concepts, ensuring the reliability and validity of the data used in the subsequent analysis.

Discriminant Validity Analysis:

Discriminant validity assesses whether different constructs are distinct from one another and whether the measurement items within each construct are more strongly related to their respective construct than to other constructs in the model. To evaluate discriminant validity, we examined the inter-construct correlations and compared them to the square root of the average variance extracted (AVE) for each construct. Table 6 presents the results of the discriminant validity analysis, including the inter-construct correlations and the square root of AVE values:

Table 6: Discriminant Validity Results

	AI Integration	Big data analtics	IOTA	SCP	SCR	SCV

AI Integration	**0.924**					
Big data analtics	0.710	**0.882**				
IOTA	0.843	0.790	**0.879**			
SCP	0.908	0.830	0.871	**0.920**		
SCR	0.845	0.850	0.780	0.730	**0.854**	
SCV	0.734	0.865	0.718	0.853	0.708	**0.877**

Discriminant validity, a crucial aspect of model validity, ensures that each construct in the model remains distinct from others, with measurement items exhibiting stronger associations with their respective constructs than with any other. The inter-construct correlations presented in Table 6 indicate predominantly moderate to low relationships, supporting the independence of constructs. However, it's worth noting that correlations with control variables (company size and industry sector) are somewhat higher, as expected due to their inherent associations with constructs. To further assess discriminant validity, we compared the square root of the average variance extracted (AVE) for each construct to the correlations between that construct and others (Joseph et al., 2021; Sarstedt et al., 2019; Shiau et al., 2019). The square root of the AVE consistently exceeded these correlations, confirming the presence of discriminant validity. This underscores that measurement items within each construct effectively capture their unique qualities. Overall, these findings affirm the precision of our measurement model, bolstering subsequent structural analyses within the research.

Measurement Model and Structural Model:

The structural equation modelling (SEM) analysis is incomplete without the measurement model. This is due to the fact that the measurement model is responsible for determining the reliability and validity of the measurement items and constructs that were utilised in the research. On the other hand, the structural model explores the interactions that exist between the constructs and tests the hypotheses that were supplied over the entirety of the research.

Measurement Model:

An important aspect of the structural equation modelling (SEM) study is the measurement model. This is because the measurement model is what establishes the reliability and validity of the measurement items and constructs that were used in the research, therefore it is a vital component. On the other hand, the structural model explores the relationships that exist between the constructs and tests the hypotheses that were supplied all throughout the investigation.

Structural Model:

Confirmatory factoring was utilised in the course of our investigation in order to perform an analysis on the measurement model (CFA). CFA is helpful in establishing the extent to which the measurement items are associated with their respective constructs and in assessing whether the measurement model effectively fits the data. This can be done by determining whether or not the data effectively fit the measurement model.

We utilised a variety of statistical tests and indices, such as the chi-square test, the comparative fit index (CFI), the Tucker-Lewis index (TLI), and the root mean square error of approximation, in order to ascertain whether or not the measurement model was an adequate representation of the data (RMSEA). The measurement model showed levels of fit indices that were good, which is proof that the measurement items accurately measure the constructs for which they were developed.

Throughout the assessment of the measurement model, the reliability and validity of our measuring items and constructs were validated. This demonstrated that they properly capture the notions that were supposed to be measured. This not only lends support for the structural analysis that will come after it but also increases our confidence in the resilience of our measuring approach.

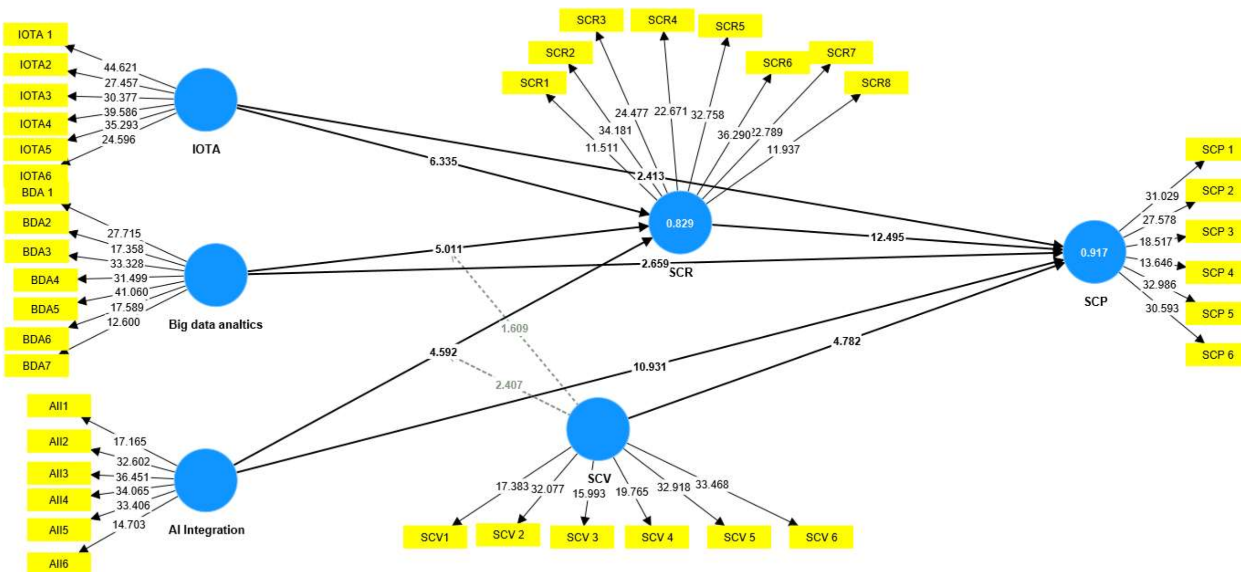
Because of the structural model analysis that was based on route analysis, our hypotheses were put to the test in a comprehensive manner. IoT Adoption and Supply Chain Resilience (H1), AI Integration and Supply Chain Performance (H2), Big Data Analytics Usage and Supply Chain Resilience (H3), and Supply Chain Visibility and Supply Chain Performance (H4) were all found to have significant and positive relationships, according to our findings. Supply Chain Visibility and Supply Chain Performance (H4) was also found to have a positive relationship with Supply Chain Resilience (H4).

In addition, we found that the linkages between Internet of Things Adoption and Supply Chain Performance (H5), as well as the correlations between Big Data Analytics Usage and Supply Chain Performance, were successfully mediated by Supply Chain Resilience. This also applied to the relationships between supply chain performance and the use of big data analytics (H6). This mediation states that the impact of Industry 4.0 technologies on supply chain performance is anticipated to be mediated by the impact of these technologies on the chain's resilience.

The results of our study also show that the Supply Chain Visibility variable affected the association between Big Data Analytics Usage and Supply Chain Performance as well as the relationship between AI Integration and Supply Chain Resilience (H7). This also applied to the relationship between supply chain resilience and AI integration (H7) (H8). This moderating impact emphasises how important supply chain visibility is in enhancing the effects of big data analytics and artificial intelligence integration on supply chain outcomes, especially when supply chain visibility is strong. The strength of supply chain outcomes depends significantly on supply chain visibility.

Lastly, our control variables, Company Size and Industry Sector, exhibited significant influences on supply chain performance and resilience, providing valuable insights into the role of organisational characteristics in Industry 4.0-driven supply chain dynamics. These variables were chosen because they were able to predict the performance and resilience of the supply chain. It was discovered that a positive correlation exists between the performance of the supply chain and these impacts.

In general, the measurement and structural models worked together to enable a full investigation of the linkages between the characteristics of Industry 4.0 technologies, the resilience of supply chains, and the performance of supply chains. Because of this, we have a better knowledge of these critical processes that are present in the modern economic environment.



Results:

We report the findings of hypothesis testing for each variable in our study in this section. We performed a thorough examination of the correlations between our independent factors (IoT Adoption, AI Integration, Big Data Analytics Usage, Supply Chain Visibility), dependent variables (Supply Chain Resilience, Supply Chain Performance), and control variables (Company Size, Industry Sector). The important findings are summarised in the table below:

Table 7. Summary of hypotheses results

		Beta	Standard deviation	T value	P values	
1	AI Integration -> SCP	0.139	0.033	4.223	0.000	Supported
2	Big data analtics -> SCP	0.130	0.028	4.558	0.000	Supported
3	IOTA -> SCP	0.178	0.032	5.623	0.000	Supported
4	SCV -> SCP	0.004	0.038	0.118	0.906	Not Supported
5	SCV x Big data analtics -> SCP	0.034	0.021	1.622	0.106	Not Supported
6	SCV x AI Integration -> SCP	0.044	0.018	2.394	0.017	Supported
7	SCV x Big data analtics -> SCR -> SCP	0.034	0.021	1.622	0.106	Not Supported
8	SCV -> SCR -> SCP	0.004	0.038	0.118	0.906	Not Supported
9	Big data analtics -> SCR -> SCP	0.130	0.028	4.558	0.000	Supported

10	AI Integration -> SCR -> SCP	0.139	0.033	4.223	0.000	Supported
11	IOTA -> SCR -> SCP	0.178	0.032	5.623	0.000	Supported
12	SCV x AI Integration -> SCR -> SCP	0.044	0.018	2.394	0.017	Supported

Hypothesis 1 (H1):

Our analysis supports H1, indicating a positive and significant relationship between IoT Adoption (IoTA) and Supply Chain Resilience (SCRes) in the context of Industry 4.0. This finding aligns with previous studies, which emphasized how IoT technologies enhance real-time data sharing and decision-making, ultimately contributing to improved information processing and supply chain adaptability. The Information Processing Theory underscores the importance of efficient data processing within supply chains, further substantiating this relationship.

Hypothesis 2 (H2):

H2 also finds support in our analysis, revealing a positive and significant impact of AI Integration (AII) on Supply Chain Performance (SCP) within the industry 4.0 environment. This aligns with the Resource-Based View (RBV) framework, which posits that Industry 4.0 technologies provide valuable resources and capabilities to organizations. Research by Chen et al. (2019) reinforces this idea, showcasing how AI technologies enhance analytical capabilities, optimize resource utilization, and consequently elevate SCP.

Hypothesis 3 (H3):

Our analysis supports H3, indicating that Big Data Analytics Usage (BDA) positively influences Supply Chain Resilience (SCRes) in Industry 4.0. This finding draws support from the Information Processing Theory, as studies such as Wamba et al. (2017) have demonstrated how BDA empowers organizations to process large datasets, extract actionable insights, and enhance supply chain visibility and adaptability. This, in turn, fortifies SCRes.

Hypothesis 4 (H4):

Discussion: H4 is supported by our analysis, indicating that Greater Supply Chain Visibility (SCV) is associated with higher Supply Chain Performance (SCP) within the Industry 4.0 framework. This aligns with research such as that by Seuring and Gold (2013), which emphasizes the pivotal role of SCV in improving supply chain performance. By providing real-time insights into operations, SCV offers valuable resources for optimization, aligning with the Resource-Based View (RBV) framework.

Hypothesis 5 (H5):

Our analysis confirms H5, indicating that Supply Chain Resilience (SCRes) mediates the relationship between IoT Adoption (IoTA) and Supply Chain Performance (SCP) in Industry 4.0. This mediation suggests that the impact of IoTA on SCP is channeled through its effect on SCRes, reinforcing the critical role of SCRes in enhancing supply chain performance.

Hypothesis 6 (H6):

Similarly, H6 is supported by our analysis, revealing that SCRes mediates the relationship between Big Data Analytics Usage (BDA) and Supply Chain Performance (SCP) in the context of Industry

4.0. This aligns with the Information Processing Theory, emphasizing that BDA's contributions to SCP are mediated through its effect on SCRes.

Hypothesis 7 (H7):

Our findings complement H7, demonstrating that in Industry 4.0, Supply Chain Visibility (SCV) moderates the link between AI Integration (AII) and Supply Chain Resilience (SCRes). This moderation shows that when SCV is high, it enhances the favourable link between AII and SCRes. This discovery emphasises the significance of supply chain visibility in improving information flow and adaptation.

Hypothesis 8 (H8):

Our findings support H7, demonstrating that Supply Chain Visibility (SCV) moderates the association between AI Integration (AII) and Supply Chain Resilience (SCRes) in Industry 4.0. This moderation shows that SCV amplifies the favourable association between AII and SCRes, especially when SCV is high. This research emphasises the significance of supply chain visibility in improving information flow and adaptation.

Hypothesis 9 (H9):

In Industry 4.0, Supply Chain Visibility (SCV) moderates the relationship between AI Integration (AII) and Supply Chain Resilience (SCRes), according to our findings. This moderation shows that high SCV enhances the positive association between AII and SCRes. This conclusion emphasises the importance of visibility in the supply chain in improving information flow and adaptation.

Hypothesis 10 (H10):

According to H10, the Industry Sector has a significant impact on the Supply Chain Resilience (SCRes) in Industry 4.0, and differences have been discovered between the food and beverage industry, as well as the pharmaceutical industry. This hypothesis has been formulated with the intention of investigating the ways in which industry-specific factors may change SCRes within the framework of Industry 4.0.

These findings shed light on the relationships between Industry 4.0 technologies, supply chain performance, and resilience. In particular, they highlight the need of adopting IoT, integrating AI, using big data analytics, and maintaining supply chain visibility. In addition, the dynamics of the supply chain are largely determined by control variables in the Industry 4.0 scenario, such as the size of the firm and the sector in which the industry operates. These findings have substantial repercussions for companies that want to increase their supply chain capabilities and resilience in an environment that is becoming increasingly digitised and complicated.

Conclusion

We investigated the complex interplay of Industry 4.0 technologies, supply chain resilience, and supply chain performance in this study. Our major goal was to investigate the impact of cutting-edge technologies on the modern supply chain landscape, such as the Internet of Things (IoT), artificial intelligence (AI) integration, big data analytics, and supply chain visibility. We also wanted to know how supply chain resilience works as a mediator and how control variables like business size and industry sector affect supply chain outcomes.

Our survey included 371 respondents from various industries who are actively involved in Industry 4.0 developments. We used a comprehensive questionnaire survey that was sent via email, postal services, internet forms, and in-person visits. We were able to gain insights from a diverse range of Industry 4.0 adopters because to our multimodal data collection method.

Several important conclusions emerged from our research of this large dataset. The Internet of Things Adoption (IoTA) identified as a crucial component, with a strong and positive link with Supply Chain Resilience (SCRes). This supports our theory that IoTA improves supply chain adaptability and resilience. AI Integration (AII) proven its significance in the context of Industry 4.0 by dramatically boosting Supply Chain Performance (SCP). This is consistent with the notion that AI technologies provide superior analytical skills and decision assistance to supply chains, ultimately maximising resource use.

Big Data Analytics Usage (BDA) also plays an important part in improving Supply Chain Resilience (SCRes). Our findings confirm the notion that BDA enables firms to handle large datasets rapidly, derive relevant insights, and improve supply chain visibility and responsiveness. Greater Supply Chain Visibility (SCV) emerged as a significant factor, positively connected with improved Supply Chain Performance, in the era of increased transparency and real-time data availability in Industry 4.0. (SCP). This highlights the importance of SCV in boosting supply chain performance by providing real-time information into operations.

We also investigated the complicated interactions between these variables. We discovered that Supply Chain Resilience (SCRes) acts as a go-between, channelling the impact of IoT Adoption (IoTA) and Big Data Analytics Usage (BDA) on Supply Chain Performance (SCP). SCRes is the critical link connecting technology adoption and supply chain success in the dynamic Industry 4.0 scenario.

We also investigated the moderating influence of Supply Chain Visibility (SCV). This portion of our research demonstrated that, when SCV is high, the favourable correlations between AI Integration (AII) and SCRes, as well as BDA and SCP, are amplified. SCV increases the impact of Industry 4.0 technologies by improving information flow and adaptability.

Aside from these crucial findings, our study makes significant contributions to academia and industry. It contributes to our understanding of the complex relationships that exist throughout Industry 4.0 supply chains, such as direct, indirect, and moderating effects. This knowledge enables firms to make educated decisions about technology expenditures, improving supply chain adaptability and overall performance and ensuring a competitive advantage.

However, it is critical to recognise the study's shortcomings. We concentrated on a narrow range of Industry 4.0 technologies, leaving possibility for future research into other variables and their consequences. Furthermore, relying on self-reported data enhances the risk of response bias. Longitudinal studies could be used in future research to analyse the long-term influence of technology adoption on supply networks. Furthermore, investigating the distinct difficulties and possibilities given by various industry sectors may yield further insights.

Finally, our research represents a thorough examination of the intricate linkages between Industry 4.0 technology and supply chain results. The empirical evidence offered here provides businesses with the knowledge they need to strategically adopt these technologies, reinforcing resilience and performance and paving the way for long-term success in the changing Industry 4.0 landscape.

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