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THE IMPACT OF BIG DATA ANALYTICS CAPABILITIES ON SUPPLY CHAIN PERFORMANCE: THE ROLES OF SUPPLY CHAIN RESILIENCE AND INNOVATION IN JORDAN

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ABSTRACT

This study examines the impact of big data analytics capability on supply chain performance and investigates the mediating roles of supply chain resilience and supply chain innovation within the Jordanian manufacturing sector. Increasing uncertainty and competitive pressures have encouraged organizations to adopt data-driven capabilities to improve operational efficiency and decision-making quality. Despite the growing importance of big data analytics, empirical research has yet to examine its indirect influence on supply chain performance through resilience and innovation, particularly in emerging economies. A quantitative research design was employed, and data were collected from manufacturing firms in Jordan using structured questionnaires. The study measured big data analytics capability, supply chain resilience, supply chain innovation, and supply chain performance. Advanced statistical techniques were applied to examine both direct and mediating relationships. The findings revealed that big data analytics capability has a significant positive effect on supply chain performance. Moreover, supply chain resilience and supply chain innovation significantly mediated this relationship, strengthening the overall impact on performance outcomes. The study contributes to literature by proposing an integrated framework that links analytics capability, resilience, innovation, and supply chain performance in an emerging market context. In practice, the findings provide managers with insights into how to leverage data-driven capabilities to enhance adaptability, innovation, and operational performance.

KEYWORDS: Big Data Analytics, Supply Chain Performance, Supply Chain Resilience, Supply Chain Innovation, Manufacturing Firms.

1. INTRODUCTION

The supply chains are now working in an environment of dynamism and uncertainty, which is marked by volatility in the markets, global disruptions, and increased competition [1]. These conditions mean that firms are increasing responsiveness, visibility, and overall performance and managing risks more effectively. The traditional supply chain practices are not enough to handle such complexities, and this has prompted organizations to embrace improved digital capabilities. Of these, there has been a growing interest in big data analytics capabilities (BDAC) as a strategic resource that allows firms to acquire, process and analyze large amounts of structured and unstructured data to support informed decision making and enhance operations of the supply chain. BDAC has been at the center of enhancing some of the main supply chain functions, such as demand forecasting, inventory management, and co-ordination of suppliers [2]. Through data-driven insights, organizations can become more efficient in their operations, less uncertain, and more responsive to the changes in the market. In addition to these direct contributions, BDAC also assists in developing supply chain resilience, which is defined as the capacity of the supply chains to anticipate, absorb, and recover in case of disruption. High-level analytics enables companies to have continuity and reduce performance losses when undergoing uncertain situations. Moreover, supply chain innovation has become a very important source of competitive advantage. Innovation entails introducing new technologies, redesigning, and introducing new practices that enhance efficiency and flexibility. Firms that have high analytics are in a better position to know the emerging opportunities, develop innovation and increase the flexibility of the supply chain [3]. Consequently, innovation is a significant process by which BDAC can be translated into better performance results. Although the literature on big data analytics, resilience, and innovation, continues to grow, the existing studies tend to investigate these constructs individually, which results in a fragmented understanding of the relationships between these constructs. In addition, the empirical data in developing economies is rather scarce. The manufacturing companies in the context of Jordan are experiencing the problem of high operation costs, a lack of supply, and fluctuating demand, and are increasingly investing in digital technologies to enhance their competitiveness [4]. Nevertheless, no empirical studies have investigated the impacts of BDAC on supply chain performance in terms of resilience and innovation in this environment. Thus, this research will explore how the capabilities of big data analytics affect the performance of supply chains and examine the mediating effects of supply chain resilience and supply chain innovation on the performance of supply chains in Jordan manufacturing companies [5]. By filling this gap, the study will enhance the literature by offering a coordinated view on the digital capabilities and supply chain performance and providing practical implications to organizations aware of the need to increase their effectiveness in operations in emerging market settings.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

This section reviews the key literature related to big data analytics capabilities, supply chain innovation, supply chain resilience, and supply chain performance. In line with the study's theoretical foundation, the discussion focuses on how data integration, data quality, and technical infrastructure enable firms to improve information processing, develop innovation capabilities, strengthen resilience, and enhance supply chain performance. The section first explains the main constructs of the study and then develops the hypotheses linking these constructs based on prior empirical evidence and relevant theoretical arguments.

2.1. Data Integration

The increasing digitalization of supply chains has significantly expanded the volume, velocity, and variety of data generated across manufacturing, procurement, logistics, warehousing, and distribution activities. Big data analytics refers to the use of large and complex datasets to support more informed and timely decision-making [6]. In supply chain management, big data is particularly valuable because firms generate and exchange extensive information through sensors, RFID technologies, tracking systems, enterprise information platforms, and inter-organizational digital systems [7]. However, the value of big data does not depend only on the availability of data. Rather, it depends on the firm's ability to integrate, standardize, and transform fragmented data into actionable supply chain intelligence.

Data integration is therefore a fundamental dimension of Big Data Analytics Capabilities (BDAC). It refers to the ability of firms to consolidate data from internal functions and external supply chain partners into a unified, accessible, and analyzable system. Without integration, data remains dispersed across functional silos, limiting visibility, delaying decisions, and reducing the reliability of analytics-based insights. Previous research indicates that realizing value from big data depends not only on analytical tools, but also on the organization's ability to structure and integrate data resources effectively [7]. From the perspective of Organizational Information Processing Theory, data integration increases the firm's information-processing capacity by enabling more accurate, timely, and coordinated responses to supply chain complexity and uncertainty.

In supply chain settings, integrated data environments support real-time performance monitoring, customer communication, predictive analytics, demand forecasting, and risk mitigation. They also strengthen internal coordination between procurement, production, warehousing, and distribution units, while externally enabling closer collaboration with suppliers and customers [9]. Such alignment is particularly important in manufacturing supply chains, where disruptions, demand volatility, and supplier uncertainty require rapid access to accurate and shared information. In this regard, data integration enhances resilience by helping firms detect risks earlier, respond more quickly to disruptions, and coordinate recovery efforts. Firms with strong BDA capabilities are better positioned to manage complex tasks, recognize patterns, and improve transparency and responsiveness during disruptive events [10].

Data integration also contributes to innovation. By enabling firms to identify inefficiencies, redesign processes, optimize routes, reduce transportation costs, and develop new operating models, integrated data systems create the informational foundation for supply chain innovation. The introduction of analytics-based practices also requires complementary organizational resources, IT infrastructure, and human expertise [8]. Therefore, data integration should not be viewed as a purely technical activity, but as a strategic capability that enables firms to transform raw data into operational improvements, innovative practices, and stronger supply chain performance.

2.2. Data Quality

Although digitally enabled supply chains generate large volumes of data, the availability of data alone does not automatically lead to better decision-making or superior performance [11]. The value of BDAC depends heavily on the quality of the underlying data. Data quality refers to the extent to which data are accurate, complete, timely, consistent, reliable, and relevant to business needs. In supply chains, high-quality data are essential for operational coordination, regulatory compliance, planning, forecasting, inventory management, and customer service [12].

Manufacturing firms operating in interconnected supply chain networks are increasingly required to exchange accurate and timely product, logistics, and shipment data through business-to-business interfaces [13]. Regulatory compliance, global standardization, and inter-firm integration require precise documentation of product identifiers, dimensions, weights, safety information, and shipment descriptions. Poor-quality data may result in financial penalties, reputational damage, delivery errors, additional inspections, and weaker relationships with supply chain partners [14]. In international supply chains, inaccurate or delayed shipment information can create customs inefficiencies, documentation errors, and additional post-processing costs. The "push-left" principle highlights that data-quality responsibility should move upstream to the party that originally generates the data [15]. This emphasizes the networked nature of data quality and the need for structured Data Quality Management across supply chain actors.

From a BDAC perspective, data quality is a prerequisite for effective analytics. Big data analytics relies on statistical techniques, regression analysis, machine learning, correlations, and predictive modeling to generate actionable insights [16]. However, sophisticated analytical methods cannot compensate for inaccurate, incomplete, or inconsistent data inputs. Poor data quality weakens the reliability of analytics outputs, reduces managerial confidence, and may lead to inappropriate supply chain decisions. Data Quality Management therefore requires clear roles, governance mechanisms, policies, and procedures for data acquisition, maintenance, dissemination, and control.

Data quality is particularly challenging in supply chains because multiple actors, including manufacturers, exporters, freight forwarders, customs agents, carriers, and importers, contribute to data generation and exchange. Cross-organizational boundaries can dilute accountability, especially when activities are outsourced or governed through cost-focused contracts rather than service-level data-quality standards [17]. These conditions may increase information asymmetry, moral hazard, and adverse selection. Therefore, high-quality data strengthens the information base needed for innovation, resilience, and performance. It enables firms to identify operational problems accurately, develop new solutions, respond to disruptions, and coordinate decisions across the supply chain.

2.3. Technical Infrastructure

Technical infrastructure represents the technological foundation that allows firms to capture, store, process, analyze, and exchange supply chain information. Organizational performance is strongly influenced by the strength of its infrastructure, including managerial capabilities, financial resources, marketing capabilities, and investment strategies. Among these elements, IT infrastructure plays a central role because it enables coordination, communication, data processing, and real-time operational control across organizational functions [18]. In supply chain management, technical infrastructure supports digital connectivity, system integration, and information sharing between supply chain partners.

As supply chains become more complex and geographically dispersed, integrated IT infrastructure becomes essential for managing interconnected manufacturing, warehousing, transportation, and distribution systems [19]. A strong technical infrastructure enables fast and reliable movement of supply chain information within and beyond firm boundaries. It allows firms to standardize data definitions, maintain consistent databases, and ensure compatibility across different systems and business processes. Data consistency is especially important because inconsistent or poorly formatted information can increase operational inefficiency, distort demand signals, and amplify the bullwhip effect [20].

Cross-functional application integration is another important element of technical infrastructure. It refers to the real-time connection of internal and external functional applications, including ERP, SCM, CRM, vendor-managed inventory, and collaborative planning systems [21]. ERP systems provide the central platform for workflow automation, standard reporting, and synchronized decision-making across departments. When ERP systems are extended beyond organizational boundaries and linked with suppliers and customers, they create a digitally integrated supply chain ecosystem (Khan et al., 2023). From the Resource-Based View, such infrastructure can become a valuable and difficult-to-imitate organizational resource when combined with data, human expertise, and managerial routines. From Dynamic Capability Theory, technical infrastructure enables firms to reconfigure processes, respond to market changes, and support innovation and resilience.

Therefore, technical infrastructure is not merely a supporting tool. It is a strategic enabler of analytics-based supply chain management. It facilitates innovation by allowing firms to introduce digital processes, automated workflows, predictive systems, and collaborative platforms. It also strengthens resilience by improving visibility, traceability, responsiveness, and coordination during disruptions. Moreover, technical infrastructure can directly improve supply chain performance by reducing delays, improving accuracy, lowering coordination costs, and supporting faster decision-making.

2.4. Innovation

Innovation is a central strategic capability in contemporary supply chains, particularly in manufacturing environments characterized by technological change, global competition, and volatile demand. Innovation refers to the development and implementation of new processes, technologies, organizational practices, and collaborative mechanisms that increase value creation across the supply network [22]. In supply chains, innovation extends beyond product development and includes process innovation, digital innovation, organizational innovation, and inter-organizational innovation.

Dynamic Capability Theory provides a strong theoretical basis for understanding the role of innovation in supply chains. The theory emphasizes the ability of firms to integrate, build, and reconfigure internal and external competencies in response to changing environments [23]. Through innovation, supply chains can sense emerging opportunities, seize new market possibilities, and transform operations to sustain competitiveness. In manufacturing firms, innovation may involve advanced production technologies, digital platforms, predictive analytics, flexible production systems, and collaborative planning tools that improve responsiveness and integration [24].

Prior research indicates that supply chain integration supports innovation by enabling knowledge sharing, joint problem-solving, and collaborative development of products and processes [25]. When firms are internally integrated and maintain strong relationships with suppliers and customers, they create an environment that supports continuous improvement and diffusion of innovation. This is especially relevant for technological innovation, where digital technologies such as big data analytics, artificial intelligence, cloud computing, Internet of Things, and blockchain transform traditional supply chain operations into data-driven systems [26]. These technologies enhance transparency, forecasting accuracy, real-time decision-making, risk prediction, and process automation.

Innovation also improves supply chain flexibility. Flexible supply chains can adjust production volumes, modify product characteristics, redesign logistics networks, and respond quickly to changing demand conditions [27]. Innovation supports this flexibility through modular production systems, digital tracking, shared planning systems, and automated decision-support tools [28]. Empirical evidence suggests that innovative supply chains are more likely to achieve improved cost efficiency, delivery reliability, quality, coordination, and customer satisfaction. Practices such as collaborative forecasting, vendor-managed inventory, and ERP-SCM integration reduce operational inefficiencies and enhance coordination among supply chain partners [29]. Accordingly, innovation can be understood as a mediating capability through which analytics-related resources are converted into superior supply chain performance.

2.5. Supply Chain Resilience

Supply chain resilience has become increasingly important as supply chains face frequent disruptions caused by geopolitical tensions, pandemics, logistics delays, demand shocks, supplier failures, and technological uncertainty. Earlier supply chain risk-management literature focused mainly on identifying, assessing, managing, and monitoring risk sources. However, supply chains differ from individual organizations because they are complex networks that may include hundreds or thousands of interacting actors and relationships [30]. In such complex systems, it is unrealistic to identify all possible risks in advance. Many severe disruptions result from low-probability and high-impact events, often described as black swan events, such as major supply chain disruptions and the COVID-19 pandemic [31].

For this reason, resilience has emerged as a more appropriate perspective for managing turbulent supply chain environments. Rather than focusing only on specific risks, resilience emphasizes the ability of supply chains to prepare for, respond to, recover from, and adapt after disruptions [32]. The literature has gradually expanded from defining resilience to examining its antecedents, enabling mechanisms, and performance implications. While engineering resilience focuses on stability and rapid recovery to an original state, ecological resilience emphasizes adaptation, persistence, and transformation under changing conditions [34]. In modern supply chains, the ecological view is particularly relevant because disruptions may not simply interrupt existing operations; they may reshape markets, technologies, supplier structures, and customer expectations.

From a Dynamic Capability Theory perspective, resilience reflects the ability of supply chains to reconfigure resources and routines under uncertainty. Firms with stronger data integration, higher data quality, and better technical infrastructure are more capable of sensing disruptions, interpreting weak signals, coordinating responses, and reorganizing supply chain activities. Resilience has also been conceptualized as a capability framework. Pettit et al. argued that supply chain resilience results from the balance between vulnerabilities and capabilities, producing a "zone of resilience" in which long-term performance and profitability are more sustainable [35]. Therefore, resilience is expected to play a key role in translating analytics-related capabilities into improved performance.

2.6. Supply Chain Performance

Supply Chain Performance (SCP) refers to the extent to which supply chain operations achieve operational and strategic objectives related to efficiency, effectiveness, responsiveness, reliability, flexibility, customer satisfaction, and value creation [36]. As supply chains become more digitally connected and complex, performance measurement has shifted from isolated operational indicators toward multidimensional evaluation systems. SCP is therefore a systematic assessment of supply chain outcomes at financial, operational, relational, and strategic levels [37].

Performance cannot be assessed only through cost reduction or logistics efficiency. It also reflects the ability of the supply chain to meet customer requirements, deliver reliable service, improve quality, coordinate with partners, and sustain competitive advantage. Continuous performance measurement allows firms to identify inefficiencies, reduce process variability, improve cross-functional coordination, and support financial stability [38]. In modern supply chains, performance is strongly connected to information sharing, digital coordination, and collaboration among supply chain partners.

The literature shows that coordinated ordering, synchronized inventory, shared planning, and logistics integration contribute to shorter lead times, fewer stockouts, and improved responsiveness. SCP is therefore not only an internal firm-level construct, but also a network-level outcome resulting from inter-organizational alignment. Previous studies have used different criteria to assess SCP, including agility, sustainability, quality, customer service, coordination, operational efficiency, supplier commitment, and flexibility. Information technology has also been shown to positively influence supply chain performance, supporting the strategic role of digital capabilities in improving supply chain outcomes [39]. Accordingly, this study conceptualizes SCP as the final outcome influenced by data integration, data quality, technical infrastructure, innovation, and supply chain resilience.

2.7. Hypotheses Development

This study develops its hypotheses based on Organizational Information Processing Theory, Resource-Based View, and Dynamic Capability Theory. Organizational Information Processing Theory suggests that firms operating in uncertain and complex environments require stronger information-processing capabilities to reduce uncertainty and improve decision quality. In supply chain contexts, big data analytics capabilities enhance the ability of firms to collect, process, interpret, and share information across internal functions and external supply chain partners [6], [7]. From the Resource-Based View, data integration, data quality, and technical infrastructure can be considered strategic organizational resources when they are valuable, embedded in firm routines, and difficult for competitors to imitate [8], [18]. Dynamic Capability Theory further explains how firms use these resources to develop innovation and resilience, allowing them to adapt to environmental changes and improve supply chain outcomes [23], [35].

Accordingly, the conceptual model positions data integration, data quality, and technical infrastructure as key analytics-related antecedents; innovation and supply chain resilience as strategic supply chain capabilities; and supply chain performance as the final outcome.

2.7.1. Data Integration, Innovation, Supply Chain Performance, And Supply Chain Resilience

Data integration provides a unified informational foundation that allows firms to combine internal and external supply chain data. When data from procurement, production, warehousing, logistics, suppliers, and customers are integrated, firms are better able to identify inefficiencies, discover improvement opportunities, and develop new supply chain practices [7], [9]. Integrated data systems also support collaborative planning, process redesign, predictive decision-making, and digital innovation. Since innovation depends on timely and accessible information, firms with stronger data integration capabilities are more likely to generate and implement new supply chain solutions [22], [25].

Therefore, the following hypothesis is proposed:

H1: Data integration has a significant positive impact on innovation.

Data integration may also directly improve supply chain performance. Integrated information reduces delays, improves coordination, enhances forecasting accuracy, and supports faster decision-making across supply chain functions [9], [20]. By reducing information silos and improving visibility, firms can improve delivery reliability, operational efficiency, customer responsiveness, and cost control [36], [38].

Therefore, the following hypothesis is proposed:

H2: Data integration has a significant positive impact on supply chain performance.

Data integration is also expected to strengthen supply chain resilience. Resilient supply chains require early detection of disruptions, real-time visibility, rapid coordination, and effective recovery actions [30], [32]. Integrated data allows firms to monitor supply chain activities more effectively, identify risk signals, communicate with partners, and respond quickly to disruptions [10], [35].

Therefore, the following hypothesis is proposed:

H3: Data integration has a significant positive impact on supply chain resilience.

2.7.2. Data Quality, Innovation, Supply Chain Performance, And Supply Chain Resilience

High-quality data is essential for innovation because innovation depends on reliable insights. When data are accurate, complete, timely, and consistent, managers can better identify market trends, operational problems, customer needs, and process improvement opportunities [11], [12]. Poor-quality data may mislead decision-makers and reduce confidence in analytics-based innovation. Since big data analytics relies on reliable inputs to generate useful insights, firms with higher data quality are more likely to introduce effective supply chain innovations [16], [22].

Therefore, the following hypothesis is proposed:

H4: Data quality has a significant positive impact on innovation.

Data quality is also expected to improve supply chain performance. Accurate and timely data improve forecasting, inventory planning, production scheduling, shipment documentation, and customer service [12], [13]. In contrast, poor-quality data may lead to errors, delays, unnecessary costs, regulatory problems, and weak coordination among supply chain partners [14], [15]. Therefore, reliable data provides the informational foundation needed to improve supply chain efficiency and effectiveness [36], [39].

Thus, the following hypothesis is proposed:

H5: Data quality has a significant positive impact on supply chain performance.

Data quality further contributes to resilience. During disruptions, managers require accurate, complete, and timely information to understand the nature of the disruption, assess its consequences, and coordinate responses [31], [32]. Inaccurate or incomplete data may delay recovery and increase operational uncertainty. High-quality data therefore enables firms to detect risks earlier, make better recovery decisions, and maintain continuity during disruptions [15], [35].

Therefore, the following hypothesis is proposed:

H6: Data quality has a significant positive impact on supply chain resilience.

2.7.3. *Innovation And Supply Chain Performance*

Innovation enables firms to improve supply chain processes, adopt new technologies, redesign logistics activities, enhance collaboration, and respond more effectively to changing customer and market requirements [22], [24]. Innovative supply chains are more capable of reducing costs, improving delivery reliability, enhancing flexibility, and increasing customer satisfaction [27], [29]. From a Dynamic Capability Theory perspective, innovation allows firms to reconfigure supply chain resources and processes to achieve superior outcomes in dynamic environments [23].

Therefore, the following hypothesis is proposed:

H7: Innovation has a significant positive impact on supply chain performance.

2.7.4. *Supply Chain Resilience and Supply Chain Performance*

Supply chain resilience improves performance by enabling firms to prepare for, respond to, recover from, and adapt after disruptions [30], [32]. Resilient supply chains can reduce downtime, maintain service levels, protect customer relationships, stabilize operations, and minimize financial losses [31], [35]. In uncertain environments, resilience is not only a defensive capability but also a strategic capability that supports continuity, responsiveness, and long-term competitiveness. Since supply chain performance depends on the ability to maintain efficiency, reliability, and responsiveness under uncertainty, resilience is expected to enhance performance outcomes [36], [38].

Therefore, the following hypothesis is proposed:

2.7.5. *Technical Infrastructure, Innovation, Supply Chain Performance, And Supply Chain Resilience*

Technical infrastructure provides the digital foundation for analytics, integration, automation, and inter-organizational connectivity. Strong IT infrastructure enables firms to adopt advanced technologies, connect internal and external systems, and support digital process transformation [18], [19]. It also facilitates experimentation with new tools such as ERP-SCM integration, predictive analytics, cloud platforms, IoT applications, and collaborative planning systems [21], [26]. Therefore, technical infrastructure is expected to support innovation.

Accordingly, the following hypothesis is proposed:

H9: Technical infrastructure has a significant positive impact on innovation.

Technical infrastructure may also directly improve supply chain performance by enabling faster information exchange, better coordination, real-time monitoring, automated workflows, and more accurate decision-making [18], [21]. Firms with stronger technical infrastructure can reduce operational inefficiencies, improve responsiveness, and enhance supply chain visibility [20], [39].

Therefore, the following hypothesis is proposed:

H10: Technical infrastructure has a significant positive impact on supply chain performance.

Finally, technical infrastructure is expected to strengthen supply chain resilience. Digital platforms, integrated systems, and real-time monitoring tools allow firms to detect disruptions, trace supply chain activities, communicate quickly with partners, and coordinate recovery actions [19], [21]. In this sense, technical infrastructure enhances the firm’s ability to sense, respond, and adapt under uncertainty, which is central to supply chain resilience [32], [35].

Therefore, the following hypothesis is proposed:

H11: Technical infrastructure has a significant positive impact on supply chain resilience.

Therefore, the following conceptual model has been suggested.

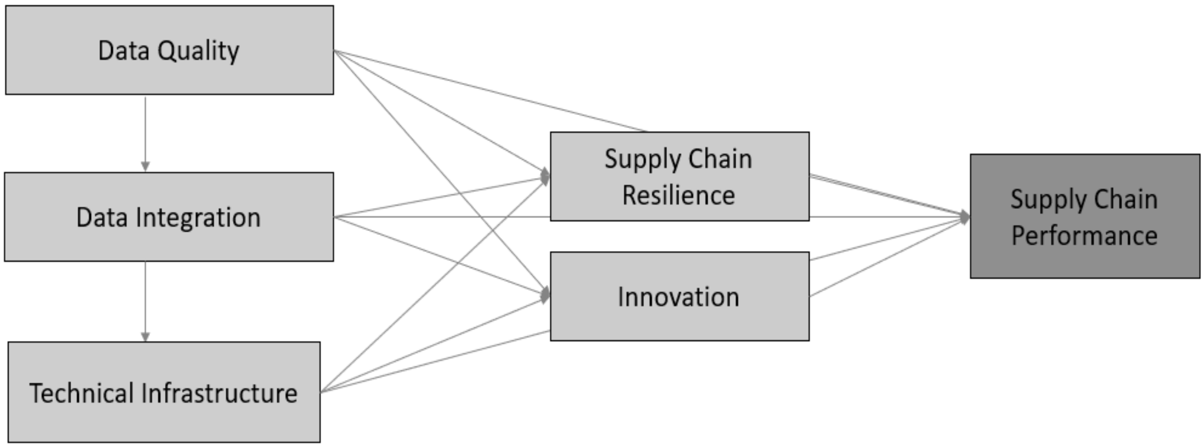

Figure 1 : Research Model

Figure 1: Conceptual Framework.

Figure 1 illustrates the conceptual model and hypotheses that are developed above to achieve the study aim and objectives.

3. METHODOLOGY

Methodology is the systematic procedures and techniques to conduct research and leads to the collection, analysis, and interpretation of data to answer the research problem. It offers a systematic framework that will guarantee validity and reliability of findings, and it allows developing and testing hypotheses in accordance with the objectives of the study. This paper takes a consistent methodological design by integrating research strategy, data collection, sampling and analytical procedures to test the relationships between big data analytics capabilities, supply chain resilience, innovation, and supply chain performance. The design of the quantitative research was used to offer a structured and objective methodology of testing the proposed hypotheses. This design provides a clear roadmap of how to answer research questions by establishing data sources, measurement procedures, and methods of data analysis. It allows exploring the correlation between variables, such as data integration, data quality, technical infrastructure, supply chain resilience, innovation, and supply chain performance in manufacturing companies. The research takes a deductive method in which the hypotheses are deduced based on the existing theories and tested using numerical data. Quantitative research is based on the standardized data collection and data analysis, which enables the results to be generalized to a larger population. This methodology helps to establish patterns and relationships among variables using strict statistical and graphical analysis. Even though qualitative research would be the most appropriate in this study because it aims at testing hypotheses and quantifying connections, its use in this study was not adopted. Instead, the quantitative methodology was deemed more suitable to achieve the objectives of the study, to ensure consistency, reliability and generalizability of the findings.

3.1. Research Approach – Research Strategy

A research approach is described as the overall approach a researcher takes as he seeks to undertake a study or research query. This research strategy refers to the methodological connection between philosophy and further selection of methods to gather and process data. These are some of the research methods and they have their merits and demerits. The choice of an approach is determined by the essence of the research question, the resources at the disposal of the researcher, and his Practically, numerous research studies apply a blend of research methods to respond to research questions because application of unique combination of research methods can bring uniformity in the research framework. The research design needs to use one or more research strategies to ensure consistency in a research project Nevertheless, the choice taken regarding the research strategy and tactics will influence the choice of the suitable time frame. The research question should be handled with an adequate research method that will be capable of yielding reliable and valid data. A survey is a research methodology that is used to collect data in a systematic manner on a large group of the population. Although the term survey is more commonly applied to refer to questionnaires, there are other such techniques, structured interviews and observations. The data gathering will usually be planned and laid out in a manner that will help analyze and interpret the data. The deductive research approach is normally associated with the survey strategy which is a common business and management strategy. It is frequently used to address questions concerning what, who, where, how much, and how many, allowing the researcher to gather the data that can be analyzed quantitatively through the descriptive and inferential statistics. The use of questionnaire-based surveying is highly trendy as it enables collection of standardized data of numerous participants which can be easily compared and is cost-effective. Moreover, the survey methodology is believable to the general population and is rather simple to understand and convey. The data collected using the survey techniques would be used to suggest possible reasons behind certain relationships between variables and develop models to describe these relationships. Survey strategy may give perfect control over research. When the probability of sampling is used, one will get statistically significant results that are representative of the whole population at a reduced cost compared to the cost of collecting data of a whole population. Nevertheless, time should be spent on making sure that the sample is representative, developing and pilot testing the data collection tool, and aiming at achieving a high response rate. The research design employed in this study was a survey strategy, which created a satisfactory degree of coherence of quantitative research with a questionnaire method of data collection, data analysis, and support of the importance of a clear research question and the achievement of the research aim and objectives.

3.2. Population And Sample

The definition of the population was a collective of individuals or objects that possess similar attributes of interest to researchers and inquirers. Researchers may simply have too many individuals to examine and thus a sample is employed. A sample is a section of the population that is chosen to be involved in research. The selection of the sample is a meaningful and reasonable sampling of the population that must be in relation to the research question and objectives (Yiduo & Jichang, 2024), the sample characteristics should be representative of the population .The study population will include people in the organizations who will not be managers, first-line managers, middle managers, and top managers involved in different manufacturing sectors in Jordan. The sample analysis of the research population instead of the whole population is likely to produce more accurate results, It is important to choose a representative and an accurate sample so that the results of the survey could be extrapolated to a greater population. Another factor to consider is the sample size, which tends to increase accurate results with the increase of the sample size. Recruiting and analyzing is however more time consuming, resource consuming and resource consuming. The sample must have 0.5 as the maximum margin of error in both directions at a 95% confidence level (Newton, 2024). The sampling design is represented by two major forms, the probability sampling and the non-probability sampling. Probability sampling can be defined as a random sampling technique when all individuals or possibilities of any case in the population have known, non-zero and equal and independent probability of being chosen. Non-probability sampling, on the other hand, is a non-random sampling method. One of the non-probability sampling types is purposive sampling in which the researcher makes decisions on which cases are to be included in the sample based on valid research responses to research questions and on the research aim and objectives. This research adopted the purposive sampling technique whereby sample of respondents was assembled in several industrial sectors in Jordan. This research was aimed at 700 respondents who were either directly or indirectly engaged in the objective of the present study, with each having a unique job title and level, manufacturing managers, production managers, plant managers, purchasing managers, operations manager, sales manager and logistics and supply chain manager. The two sources of data are primary and secondary data. Primary data is the data that is gathered at the source of a certain research project, surveys, interviews, experiments, or observation. In the case where secondary data is the description of the existing information that has been gathered by some other researchers already and could be used to support or supplement what the research is being conducted, academic journals or market research reports. The data presented in this thesis was gathered as primary data through managers and experts operating in the manufacturing companies of Jordan and secondary data through scholarly articles and other credible databases pertaining to data integration, data quality, innovation, technical infrastructure, supply chain resilience, and supply chain performance.

3.3. Reliability And Validity in This Research

The instrument is a critical factor in measuring the quality of the measurement process as validity and reliability are necessary. Validity is the degree to which an instrument is appropriate in measuring what it is designation. In the given research article, validity was determined based on the content and construct validity. The issue of content validity is whether the items of the questionnaire are sufficient to address the goal of the study and the concepts of the research. There were two ways in which it was established. The first one is a literature review, which helped in making a choice of measurement items based on credible sources. Second, the questionnaire was checked by a consortium of professionals to test the accuracy, significance, and suitability of the items, and their responses were applied to the instrument to improve it. Construct validity is the capability of the questionnaire items to reflect the exact thoughts of the constructs being measured. It was tested using convergent and discriminant validity. Convergent validity also examines the relationship of items that measure the same construct at a strong level and is usually measured by factor loading and average variance extracted (AVE) with a 0.70 and 0.50 threshold, respectively. Discriminant validity evaluates the empirical difference between each of the constructs in the measurement model. The outcome of convergent and discriminant validity is displayed. Reliability is the ability of the instrument to give consistent results. Even though reliability alone does not determine validity, it is necessary to have a good measurement Reliability can be measured with the help of test-retest reliability and internal consistency.

4. DATA ANALYSIS AND DISCUSSION

This investigates the impact of data integration on innovation, supply chain performance and supply chain resilience, effect of data quality on innovation, supply chain performance and supply chain resilience, effect of technical infrastructure on innovation, supply chain performance and supply chain resilience and finally the effect of Innovation and supply chain resilience on supply chain performance of manufacturing firms in Jordan. In the analysis, the impact of multi-item constructs is examined using Structural Equation Modelling (SEM) based on the methodology of Smart-PLS, which is the best method for dealing with this issue. Other methods are flexible such as PLS-SEM, which can be used for exploration, confirmatory and predictive models. The reliability and validity of the measurement scales are explored in the first part of the analysis, while the result of the test of the hypotheses related to the research question is displayed in the second part of the analysis.

4.1. Data Analysis

To measure the reliability of the measurement scales, internal consistency reliability tests were used with the help of Cronbach alpha and Composite Reliability (CR). All the coefficients of Cronbach's alpha of the constructs exceed the recommended value of 0.7, which means the high degree of internal consistency (Shah, 2024). Also, all the constructs Composite Reliability (CR) are above the recommended 0.7, which also confirms the reliability of the measurement scales (Guo et al., 2024. The data of the internal reliability tests are represented in Table 1.

Table (1): Constructs Validity.

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	AVE
Data Integration	DI1	0.825	0.863	0.901	0.646
	DI2	0.811			
	DI3	0.808			
	DI4	0.788			
	DI5	0.785			
Data Quality	DQ1	0.789	0.874	0.904	0.612
	DQ2	0.772			
	DQ3	0.771			
	DQ4	0.797			
	DQ5	0.750			
	DQ6	0.813			
Innovation	INN1	0.830	0.863	0.907	0.708
	INN2	0.855			
	INN3	0.834			
	INN4	0.847			
Supply Chain Performance	SCP1	0.853	0.880	0.910	0.628
	SCP2	0.823			

	SCP3	0.726			
	SCP4	0.816			
	SCP5	0.683			
	SCP6	0.838			
Supply Chain Resilience	SCR1	0.788	0.861	0.900	0.643
	SCR2	0.790			
	SCR3	0.821			
	SCR4	0.759			
	SCR5	0.848			
Technical Infrastructure	TI1	0.795	0.875	0.906	0.616
	TI2	0.736			
	TI3	0.784			
	TI4	0.759			
	TI5	0.773			
	TI6	0.857			

The assessment results of the measurement model show that the results of all study constructs have acceptable levels of reliability and convergent validity. The factor loads of the measurement items were above 0.70 in most cases (0.683 to 0.857), which is an acceptable indicator reliability level. The Cronbach's Alpha for the constructs was between 0.861 and 0.880, which is above the minimum value of 0.70, indicating good internal consistency reliability among the constructs. Likewise, Composite Reliability (CR) ranged from 0.900 to 0.910, which are high values indicating that construct reliability is high and the items of the measurement are consistent to measure the construct. In addition, the Average Variance Extracted (AVE) values were found to be between 0.612 and 0.708, which are higher than the minimum criterion of 0.50, thus showed good convergent validity and confirmed that all indicators on each construct explained more than 50% of the construct's variance. In general, the results showed good evidence for reliability and convergent validity of the Data Integration, Data Quality, Innovation, Supply Chain Performance and Technical Infrastructure measurement models.

Table (2): Discriminant Validity Assessment Htmt.

	Data Integration	Data Quality	Innovation	Supply Chain Performance	Supply Chain Resilience	Technical Infrastructure
Data Integration						
Data Quality	0.432					
Innovation	0.568	0.282				
Supply Chain Performance	0.315	0.369	0.480			
Supply Chain Resilience	0.610	0.381	0.621	0.607		
Technical Infrastructure	0.525	0.410	0.570	0.361	0.356	

Table (2) shows the discriminant validity evaluation based on Heterotrait–Monotrait Ratio (HTMT) criterion. All construct levels of the HTMT were below the recommended threshold of 0.85, which can be interpreted as an acceptable discriminant validity of the measurement model. In particular, the HTMT values varied from 0.282 to 0.621, with the highest value between Innovation and Supply Chain Resilience (0.621), which is still below the threshold. The results are consistent with the constructs being measured empirically, different from each other and measuring different conceptual phenomena, as predicted: Data Integration and Data Quality are different, as are Innovation and Supply Chain Performance, Supply Chain Resilience and Technical Infrastructure. Thus, the results in this research are able to support the adequacy of the discriminant validity and the fulfillment of the requirements of the HTMT for the measurement model.

Table (3): Discriminant Validity Farnell–Larker Criterion.

	Data Integration	Data Quality	Innovation	Supply Chain Performance	Supply Chain Resilience	Technical Infrastructure
Data Integration	0.804					
Data Quality	0.379	0.782				
Innovation	0.493	0.246	0.842			

Supply Chain Performance	0.284	0.340	0.423	0.792		
Supply Chain Resilience	0.531	0.338	0.539	0.544	0.802	
Technical Infrastructure	0.464	0.360	0.509	0.320	0.320	0.785

The discriminant validity test is performed by the Fornell–Larcker criterion as shown in Table (3). The diagonal values show Average Variance Extracted (AVE), and the square root of them are higher than the other correlations in the rows and columns of each construct, except for the correlation between the constructs A and B in the first row and column, which is higher. In particular, the diagonal values of Data Integration (0.804), Data Quality (0.782), Innovation (0.842), Supply Chain Performance (0.792), Supply Chain Resilience (0.802) and Technical Infrastructure (0.785) are higher than their inter-construct correlation values. The results of the study support the discriminant validity of each construct and the empirical distinctiveness of each construct in the model. The results thus confirm that the measurement model might be acceptable according to Fornell–Larcker criterion, which is an acceptable level of construct differentiation and validity of the conceptual framework proposed.

Table (4): R-Squared Adjusted.

	R-square	R-square adjusted
Innovation	0.343	0.333
Supply Chain Performance	0.358	0.342
Supply Chain Resilience	0.306	0.295

The endogenous constructs are presented in terms of coefficient of determination (R^2) and adjusted R^2 values in Table (4). The R^2 values in PLS-SEM represent the percentage of variance in the dependent construct accounted for by the predictor constructs, with 0.75, 0.50 and 0.25 considered as strong, moderate and weak explanatory power, respectively. The results show that the R^2 value for Innovation is 0.343 and the adjusted R^2 value is 0.333 which means that only about 34% of the variance in Innovation is explained by the independent variables. This indicates a moderate degree of explanatory power; that is, data integration and technical infrastructure provide some contribution to the model's innovation. Likewise, Supply Chain Performance had an R^2 of 0.358 and an adjusted R^2 of 0.342, indicating that almost 36% of the variance in Supply Chain Performance is accounted for by its predictor constructs. This result indicates a moderate predictive power of the structural model in explaining supply chain performance outcomes, via the interaction of data quality, data integration, innovation, supply chain resilience, and technical infrastructure. Moreover, R^2 value is 0.306 and an adjusted R^2 value is 0.295 which means that about 31% of the variance in Supply Chain Resilience is explained by the model variables. Within this proposed framework, this result is also a moderate level of predictive accuracy. The slight differences of the R^2 and adjusted R2 values of each endogenous construct suggest stability in the structure and that there is no significant overfitting because of too many predictors. Overall, the results confirm that the proposed model has an acceptable and moderate explanatory power in the framework of the supply chain management, in explaining the Innovation, Supply Chain Performance and Supply Chain Resilience. The endogenous constructs are presented in terms of coefficient of determination (R^2) and adjusted R^2 values in Table (8). PLS-SEM R^2 values have been used to explain the variance of dependent construct to dependent independent constructs: If R^2 is ≥ 0.75, it is a strong value; if R^2 is ≥ 0.50, it is a medium value; if R^2 is ≥ 0.25, it is a weak value. The results will reveal that the R^2 value of the model of Innovation is 0.541 and adjusted R^2 is 0.537, meaning that the model accounts for about 54% of the variance, or unexplained error, in Innovation. Similarly, Supply Chain Performance has an R^2 of 0.564 and an adjusted R^2 of 0.562, meaning that there is about 56% variance in the Supply Chain Performance measure explained by the predictors. The values are classified as a moderate to good level of explanatory power, and this is acceptable for research in the area of supply chain and management. Minimal differences between R^2 and adjusted R^2 for both constructs suggest stability of the model and lack of overestimation because of an oversupply of predictors. Overall, the results show that the structural model is good in explaining the phenomena, particularly in explaining the variable of Innovation and Supply Chain Performance.

Table (5): Structural Model Results (Bootstrapping).

#	Hypo	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
H1	Data Integration -> Innovation	0.329	0.064	5.174	0.000
H2	Data Integration -> Supply Chain Performance	0.110	0.076	1.454	0.146
H3	Data Integration -> Supply Chain Resilience	0.447	0.066	6.761	0.000
H4	Data Quality -> Innovation	-0.008	0.067	0.120	0.905
H5	Data Quality -> Supply Chain Performance	0.231	0.069	3.355	0.001
H6	Data Quality -> Supply Chain Resilience	0.147	0.062	2.354	0.019
H7	Innovation -> Supply Chain Performance	0.161	0.074	2.183	0.029
8H	Supply Chain Resilience -> Supply Chain Performance	0.443	0.066	6.724	0.000
9H	Technical Infrastructure -> Innovation	0.359	0.058	6.238	0.000
H10	Technical Infrastructure -> Supply Chain Performance	0.186	0.067	2.792	0.005
H11	Technical Infrastructure -> Supply Chain Resilience	0.060	0.075	0.789	0.430

The results of the structural model indicated several relationships between the variables of the study. Data integration demonstrated a significant positive effect on innovation ($\beta = 0.329$, $t = 5.174$, $p < 0.001$) and supply chain resilience ($\beta = 0.447$, $t = 6.761$, $p < 0.001$). The results show that organizations' integration of their data is beneficial to their innovative capacity and ability to deal with supply chain disruptions. However, data integration was not observed as a significant relationship with the operational performance outcomes ($\beta = 0.110$, $t = 1.454$, $p = 0.146$), which indicates that data integration alone may not directly affect operational performance outcomes. The findings also indicate that data quality had a significant positive impact on supply chain performance ($\beta = 0.231$, $t = 3.355$, $p = 0.001$) and supply chain resilience ($\beta = 0.147$, $t = 2.354$, $p = 0.019$). This indicates that proper, dependable and timely data play a role in enhancing the efficiency of the supply chain and its resilience. However, the data quality did not significantly affect innovation ($\beta = -0.008$, $t = 0.120$, $p = 0.905$), which means that quality data is not necessarily enough to drive innovative activities in organizations. Innovation was significant and positive ($\beta = 0.161$, $p = 0.029$, $t = 2.183$), indicating that the use of innovation practices in the supply chain has positive effects on its performance. Likewise, supply chain resilience had a significant positive impact on supply chain performance ($\beta = 0.443$, $t = 6.724$, $p < 0.001$), demonstrating that resilience attributes are crucial to maintaining and enhancing the efficiency of the supply chain in uncertain environments. As far as technical infrastructure, the results showed that it had a positive and significant effect on innovation ($\beta = 0.359$, $t = 6.238$, $p < 0.001$) and supply chain performance ($\beta = 0.186$, $t = 2.792$, $p = 0.005$). The results indicate that innovative activities and making improvements to operational performance are driven by advanced technological infrastructure. But no significant effect was observed for technical infrastructure on supply chain resilience ($\beta = 0.060$, $t = 0.789$, $p = 0.430$), suggesting that technical infrastructure alone might not provide a sufficient basis for building resilience if there are a lack of other organizational capabilities and practices. In conclusion, the results validate that data integration, data quality, innovation, and technical infrastructure are key factors for improving the performance of the supply chain and that supply chain resilience is one of the highest factors influencing the supply chain.

4.2. Discussion

This section reflects previous research and the empirical results, and explores how digital competences, innovation and resilience impact the performance of supply chains. The analysis was done by using the Structural Equation Modelling (PLS-SEM) and the measurement model was reliable and valid with acceptable Cronbach's Alpha, Composite Reliability, and factor loading, AVE, HTMT, and Fornell-Larcker criteria. The findings suggest that the role of Data Integration is in the middle of enhancing Innovation and Supply Chain Resilience. Information systems are integrated for sharing information, learning and cross functional coordination, enabling innovative results. As they do so, they also enhance the visibility and allow for a concerted response to disturbances, further strengthening resilience. The results corroborate earlier studies on the need for integrated data flows for better adaptability and responsiveness. Data Quality has a substantial positive impact on Innovation and Supply Chain Performance, underscoring the importance of having reliable and timely information to inform decisions and operate efficiently. However, there is no significant relationship between it and Supply Chain Resilience, indicating that information accuracy is not the only factor in determining the level of resilience, but rather structural and technological attributes are more important. This means that quality data needs to be enhanced with adaptive systems to truly be able to handle disruptions. Technical Infrastructure is identified as a cross-cutting enabler throughout the model and has an impact on Innovation, Resilience and Supply Chain Performance. This discovery highlights the importance of digital platforms, IT systems and technological readiness for advanced supply chain capabilities. Good infrastructure will facilitate process improvement, real-time monitoring and flexibility of the system, which will overall have a positive impact on innovation and system resilience. The influence of Innovation on the Supply Chain Performance is very pronounced, highlighting this as one of the key mechanisms that Innovation is driving digitization to better performance. Efficient, responsive and effective operations are realized by organizations which use data and technology to facilitate innovative practices. In contrast, Supply Chain Resilience has only a small positive impact on performance and has a small negative relationship. This discovery implies that there are short-term trade-offs, such as making investments in resilience as redundancy and risk buffering may decrease efficiency in the short-term. It also suggests that resilience can play a more important role in maintaining stability over the long term than in the short term. Overall, the findings indicate that digital capability can be seen as an enabling factor for Innovation and Resilience, with the latter being the main way to improve Supply Chain Performance, and that Data Integration and Technical Infrastructure are key components of digital capability. These findings highlight the necessity of making investments in data capabilities aligned with investments in technology to promote innovation and implement a balanced approach to resilience to prevent stunted performance in the short-term.

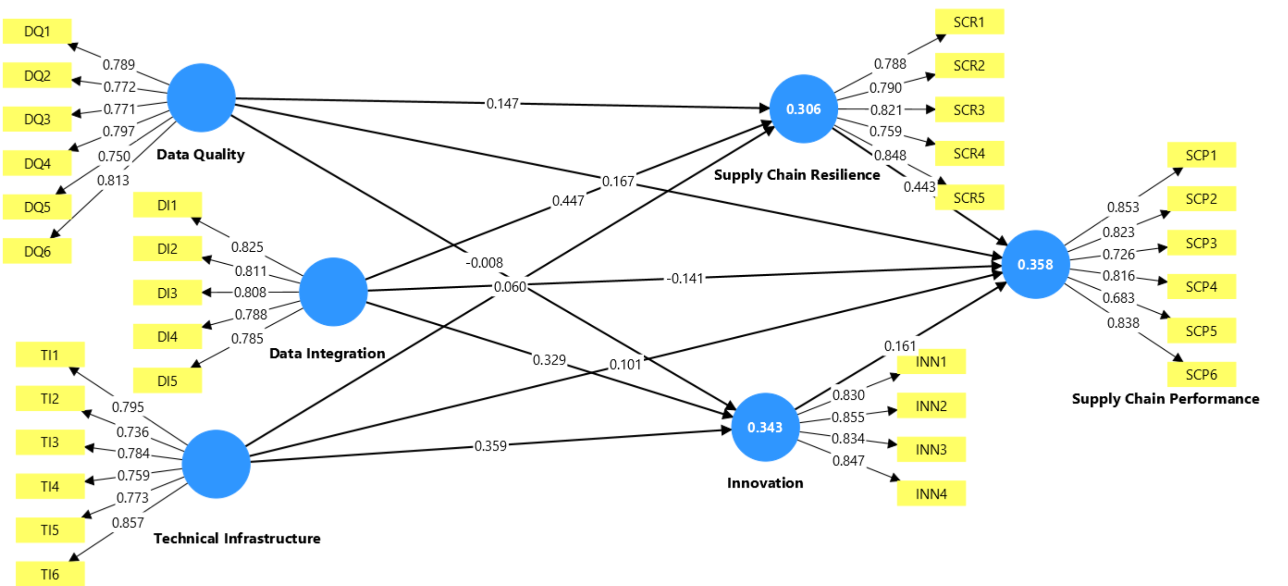

Figure 2: Hypotheses Testing Results.

5. CONCLUSIONS AND RECOMMENDATIONS

The study showed the influence of Big Data Analytics Capabilities (BDAC) on Supply Chain Performance (SCP) through a mediating role of Supply Chain Resilience (SCR), Supply Chain Innovation (SCI) in the Jordanian Manufacturing Industry (JMI). The results validate that data integration, data quality and technical infrastructure portfolios (BDAC) are key performance enhancers in uncertain, cost constrained and demand volatile supply chain environments. The findings show that data integration not only can have a positive impact on innovation but also on supply chain resilience directly affecting the performance. Firms can gain increased visibility, coordination, and responsiveness throughout the event with integrated data systems, which will help to proactively predict disruptions and make business operations more efficient. Likewise, the impact of data quality on innovation and supply chain performance – while positive – is not particularly strong when compared to the impact on resilience; this suggests that resilience is more related to structural and technological capabilities than simply to the accuracy of information. Technical infrastructure becomes a key enabler that has a major impact on innovation, resilience and performance. Advanced IT systems and digital platforms allow for the monitoring, automation and effective coordination of activities along the supply chain in real time. These capabilities enhance adaptive capacity and operational efficacy. The results also show that the innovation of the supply chain exerts a strong positive influence on performance, highlighting its role as one of the mechanisms by which BDAC manifests in measurable performance gains in efficiency, responsiveness and overall performance. By contrast, supply chain resilience does not have a direct, significant impact on performance, which could indicate short-term trade-offs or that supply chain resilience has more of an impact on long-term stability than in the short-term. The study findings indicate that innovation and resilience are driven mainly by innovation, and that data integration and technical infrastructure are key enablers of these. The results revealed the strategic need to equip the manufacturing industry with data-driven capabilities to gain sustainable competitiveness in the sector in Jordan.

5.1. Theoretical And Practical Implications

This study builds on the literature in that it combines BDAC, supply chain resilience, innovation, and performance in one. The results are empirical evidence on the mediating role of innovation and the conditional role of resilience in the emerging economy setting, whereas the previous research studied these constructs separately. The findings complement the Resource-Based View (RBV) because they show that the analytics capability is a valuable strategic resource and complement the Dynamic Capabilities Theory in that firms that successfully leverage analytics to create innovation are more likely to have higher performance outcomes. The results also highlight the need to consider BDAC as an organization's strategic capability instead of just a technological investment, from a practical perspective. To ensure Jordan's manufacturing companies prioritize: Establishing coordinated data systems for the supply chain to improve the flow of data through the supply chain Invest in strong technical foundations that enable real-time analytics and process automation. Develop solid technical infrastructure that facilitates real-time analytics and process automation. Finally, encouraging innovative practices to take analytics to a level that delivers performance gains

5.2. Developing Resilient Strategies That Are Not at the Expense of Efficiency in the Short Term.

Further, there is a need for closer interconnection in the supply chain through real-time data sharing and joint planning between partners, to enhance their responsiveness and minimize the level of uncertainty. Policymakers are urged to encourage digital transformation through strengthening the technological infrastructure, encouraging uptake of analytics, and building workforce skills. To sum up, the value of big data analytics capabilities is better manifested in innovation and resilience is a complementary capability, which is significant depending on the context. Companies that connect data initiatives with their innovation efforts are more likely to see continuous improvements in performance in a rapidly changing and unpredictable business landscape.

5.3. Research Limitation

This study presents several limitations that should be considered when interpreting the findings. First, the operationalization of Big Data Analytics Capabilities (BDAC) was limited to data integration, data quality, and technical infrastructure. Although theoretically grounded, this specification does not capture the full range of analytics capabilities and may overlook other relevant dimensions that contribute to supply chain performance. Second, the use of non-probability sampling restricts the generalizability of the results, as the sample may not fully represent the broader population of manufacturing firms in Jordan. Third, the study relied on a quantitative survey design using self-reported data, which may introduce response bias and common method variance due to single-source data collection. Fourth, the empirical analysis was confined to the Jordanian manufacturing sector, limiting the applicability of the findings to other industries and geographical contexts. Differences in economic conditions, digital maturity, and supply chain structures across sectors and countries may influence the observed relationships.

5.4. Future Research Directions

Future research can extend this study in several important ways. First, the conceptualization of BDAC can be broadened by incorporating additional dimensions, including analytical talent, data governance, artificial intelligence integration, and real-time predictive analytics, to provide a more comprehensive understanding of digital capabilities. Second, future studies may examine alternative mediating mechanisms, including supply chain agility, visibility, risk management capability, and organizational learning, to better explain how analytics capabilities influence performance outcomes. Third, the inclusion of moderating variables, including environmental uncertainty, supply chain complexity, and firm size, may help clarify the conditions under which resilience contributes to performance. Fourth, adopting probability sampling techniques would enhance the representativeness and generalizability of findings. Fifth, combining quantitative methods with qualitative or multi-source data, including interviews and archival performance measures, may improve validity and reduce bias. Sixth, longitudinal research designs are recommended to capture causal relationships over time, particularly to assess the long-term impact of supply chain resilience on performance. Finally, future studies may conduct cross-industry and cross-country comparisons, especially within the MENA region, to examine how contextual differences shape the relationships between big data analytics capabilities, supply chain resilience, innovation, and performance.

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