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Factors affecting the supply chain resilience and supply chain performance: an empirical investigation

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ABSTRACT

The key objective of this research study is to delve into the factors affecting supply chain resilience to enhance supply chain performance through the mediation of supply chain resilience. A quantitative method of research was applied to perform this particular research. Data collection was performed using the questionnaire technique. As it was impossible to collect data from every member of the targeted population, a sample of data was calculated using G*power software and a sample size of 129 respondents. It was concluded that supply chain artificial intelligence, adaptive capability, and collaboration positively and significantly influence supply chain resilience and performance. At the same time, supply chain resilience also positively impacts supply chain performance. Thus, adopting resilience and other dynamic capacities can enhance organizational and supply chain performance. This research study provides insight to the manufacturing firms' practitioners and managers for improving their resilience level in the supply chain. This specific research study plays a significant role in literature by highlighting the concept of supply chain resilience and the supply chain performance of organizations.

Keywords: *Adaptive capability, Artificial intelligence, Supply chain collaboration, Supply chain performance, and Supply chain resilience*

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Factors affecting the supply chain resilience and supply chain performance: an empirical investigation

1. Background

Every organization is at risk due to disruptions (Chaudhuri et al., 2018). The firm's resilience is defined as the capability and competency of an organization to effectively handle unexpected and unforeseen situations that always act as a central element for the firm against any disruptive condition (Cheng & Lu, 2017; Rashid et al., 2023a). On the other hand, with time, the types and number of disruptions and challenges for businesses are increasing day by day, due to which the concept of resilience is gaining more attention for its adoption and has an excellent level of significance for organizations and their management of supply chains (Fattahi et al., 2020). The disruptive supply chain of organizations may disturb the flow of services and products that the organization offers to their customers (Olivares-Aguila & ElMaraghy, 2021; Baloch & Rashid, 2022; Rasheed & Rashid, 2023). Therefore, disturbances in the supply chain system can negatively impact the firm's performance by affecting the level of stock returns and the firm's competitive position in the business environment (Ivanov & Dolgui, 2021).

Several disruptive events break down the continuous use of products and services offered by the firms. Global supply chains were disrupted by several events, including the financial crisis of 2008 and 2016, the United Kingdom's decision to leave the European Union (Brexit), and the recent worldwide pandemic of COVID-19. Therefore, to handle disruptive conditions, the concept of supply chain resilience has gained considerable attention from practitioners (Queiroz et al., 2020; Rasheed et al., 2023). Many kinds of literature based on big data analytics have established the utilization of predictive analytics for discovering the sources that cause disruptions that ultimately improve firms' supply chain systems through resilience (Choi, 2020). The organizations need to develop analytical proficiencies to increase the resilience in SC through the effective utilization of knowledge of the resident firm; in that way, organizations can strengthen their existing abilities of information (Scholten et al., 2019; Wong et al., 2020). Supply chain firms are highly investing in enhancing the level of resilience in their systems by raising the capability to manage disruptions (Sá et al., 2019) and the nonstop flow of critical supplies (Hendry et al., 2018). Effective capabilities of SC firms include forecasting and proactive management of SC threats and disturbance-creating factors and events (Baryannis et al., 2019).

Numerous investigations have identified a positive correlation between information, business, engineering, and analytics, contributing to the development of digitalization and the mitigation of supply chain (SC) risks. Various evolving technologies show promise in bolstering supply chain resilience and possess the capability to predict SC risks through advanced product tracking applications, artificial intelligence, Industry 4.0, and additive manufacturing (Ivanov & Dolgui, 2021). Earlier research has consistently portrayed AI as an up-and-coming and supportive tool for effective decision-making within the SC, fostering proactive and analytical competencies (Belhadi et al., 2019; Dhamija & Bag, 2020). The acknowledged potential of AI to facilitate decision-making processes in the SC prompts a thoughtful consideration of how artificial intelligence can be leveraged extensively to achieve long-term competitive performance in the supply chain, particularly in terms of innovation (Akter et al., 2021). Contrary to this perspective, prior studies have debated and asserted that process innovation staunchly reinforces the resilience concept in the supply chain when confronted with uncertain conditions, ultimately resulting in improved supply chain performance (Akter et al., 2021; Kwak et al., 2018). The advent of innovation propelled by artificial intelligence proves more advantageous, as it can expedite the decision-making process in prototyping, identifying, and testing solutions to disruptions (Paschen et al., 2019). This kind of decision process is an innovation that researchers call a design. The influence of invention that emerges through AI technology mainly strengthens the SC through sharing information, information processing, and integration in a firm's system. This has long been viewed as a complex factor in constructing supply chain resilience and enhancing SC performance (Wamba & Akter, 2019). Existing research studies have displayed that AI procedures have successfully encouraged innovation that offers solutions that ultimately enhance the firm's SC performance (Baryannis et al., 2019; Dubey et al., 2020).

1.1 Problem Statement

In current situations, the concept of supply chains plays an immense role in changing technology and the business atmosphere. A continuous flow of information is essential for operating supply chains in a vibrant environment with many external and internal threats that continue to overpower and destroy the level of performance (Belhadi et al., 2019; Lee et al., 2016). Moreover, the researchers Dubey et al. (2020) and Wamba et al. (2019) have identified the environment's vitality as a complex factor to be studied while handling the issue related to performance. As previously mentioned, the researcher did not test the overall model's connection among artificial intelligence, adaptive capability, and supply chain collaboration with each other and its impact on supply chain resilience. To the best of our information and knowledge, this is the first research study that empirically examines the impact of artificial intelligence on the performance of the supply chain by studying the mediating influence of supply chain resilience.

This research study will consider these market uncertainties as a problem statement. To resolve this problem, the author will incorporate the concept of supply chain resilience; the main focus of this research will be to analyze the factors behind supply chain resilience and how it enhances supply chain performance. The following research questions are considered in this study:

R1: Does artificial intelligence have a relationship with supply chain resilience?

R2: Does artificial intelligence have a relationship with supply chain performance?

R3: Does artificial intelligence have a relationship with adaptive capabilities?

R4: Does adaptive capabilities have a relationship with supply chain resilience?

R5: Does adaptive capabilities have a relationship with supply chain collaboration?

R6: Does supply chain collaboration have a relationship with supply chain resilience?

R7: Does supply chain collaboration have a relationship with supply chain performance?

R8: Does supply chain resilience have a relationship with supply chain performance?

1.2 Research Objective

The primary goal of this research is to investigate the factors influencing supply chain resilience to improve supply chain performance by incorporating the mediation of supply chain resilience. Some specific objectives of this study are given below:

O1: To test the relationship of artificial intelligence with supply chain resilience.

O2: To test the relationship of artificial intelligence with supply chain performance.

O3: To test the relationship of artificial intelligence with adaptive capabilities?

O4: To test the relationship of adaptive capabilities with supply chain resilience.

O5: To test the relationship of adaptive capabilities with supply chain collaboration.

O6: To test the relationship between supply chain collaboration and resilience.

O7: To test the relationship of supply chain collaboration with supply chain performance.

O8: To test the relationship of supply chain resilience with supply chain performance.

1.3 Significance of the Study

This study will develop a framework based on dynamic capability and supply chain resilience theories. This theory states that the firm's informational processing capability supports the organization's ability to deal with uncertain situations (Wong et al., 2020). We create a research framework mainly based on the support of a dynamic capability theory. The theoretical framework of the research study is investigated and analyzed with the help of statistical analysis that will be applied to the gathered data from manufacturing companies in Karachi. Therefore, this study will help make specific contributions, which include initially that this particular research study is the first to develop a standard of conceptual understanding about how AI-based information processing innovation influences the resilience of the supply chain and how firms can create long-term performance of SC while facing disruptive and uncertain situations with the help of capabilities based on artificial intelligence. The second contribution of the study is that it will help explain how emerging information processing innovation based on artificial intelligence could improve the high-level performance of SC and construct resilience in the operations of the supply chain through various mechanisms. Therefore, this study contributes to the theory that aims to understand how focal organizations can maintain their performance level and enhance their performance during uncertain conditions. Last but not least, the research study will cover another perspective on understanding the level of integration of AI capabilities at various stages of the supply chain to foster strong SC dynamism and collaboration. The given below figure 1 shows the structure of this research:

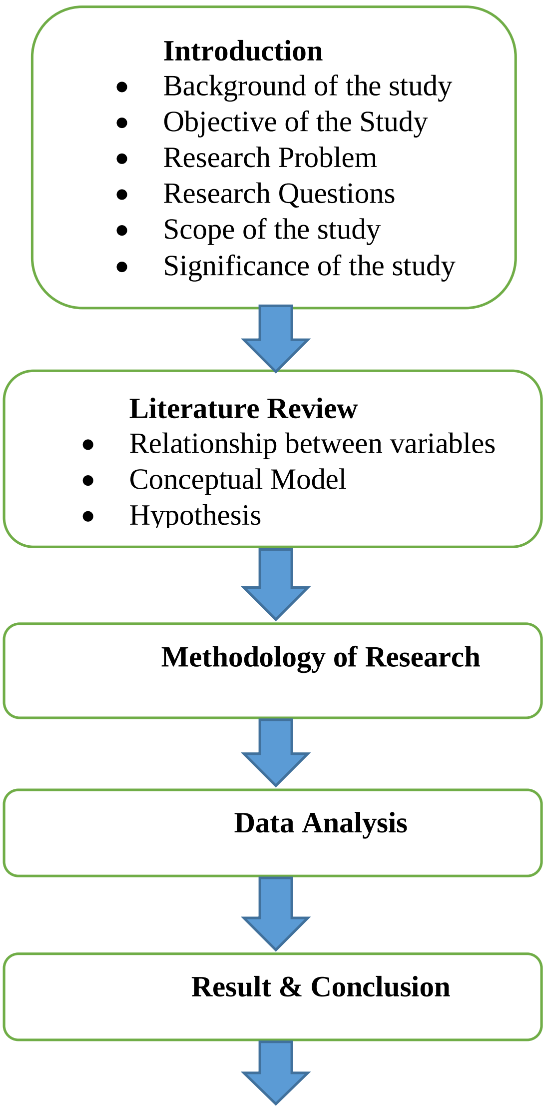

Figure 1: Structure of study

Source: Author's creation

2. Literature Review

2.1 Dynamic Capability View Theory

DCV is a great tool to analyze the resilient potentiality required in awakening the tumultuous consequences (Teece et al., 1997), an addition of the RBV (Barney, 1991; Wernerfelt, 1984). The RBV emphasizes that the firm needs to evolve its capacities to defeat trouble and attain competitive advantage. Nevertheless, a tradition of needing a proper definition of capacities is set due to dynamic changes in changeable environments. DCV addresses a customary gap in RBV by designing adequate capabilities and resources to retaliate to specific situational changes (Martin & Eisenhardt, 2000; Teece et al., 1997). Whereby covering the mannerism of eventualities.

Capacity and capability of a firm to construct, incorporate, and rearrange firms' resources, applying the procedures adopted by the firm to tackle environmental uncertainties and alterations and to outline new strategies of value creation (Martin & Eisenhardt, 2000; Teece et al., 1997). An argument can be that firms' supply chains need to develop or evolve dynamic capabilities to lessen exposure in a changeable environment, which demands flexible capabilities for long-term survival. From the standpoint of DCV, the responsive and proactive capacities and capabilities of the SCRE can be elaborated (Teece et al., 1997). DCV necessitates that organizations have the capacity and capability to incorporate, adjust, and rearrange their resources and potential to deal with quickly altering environments. Proactive scanning concerning environmental changes and attaining the requisite adaptability and flexibility should be accelerated by firms (Teece et al., 1997). According to our study, this is proportionate to the prevention of possible exposure in the supply chain and the proactive capacity of the supply chain to adjust to environmental changes. In his findings (Teece et al., 1997). This emphasizes that successful companies in the marketplace should rearrange their capabilities and resources quickly to retrieve capabilities during disruptive times. According to our argument, the reactive capability to rearrange facilities, amenities, and competencies is essential to speedily recovering from disturbance.

Pettit et al. (2019) proposed the idea of "balanced resilience," which is fundamentally the steadiness of raising costs to control susceptibilities and raise resilience capabilities. Based on the DCV, Halcomb and Ponomarov (2009) have stressed the significance of capacity and resource, particularly appropriate quantification to maintain lucrativeness by enhancing the flexibility balance. However, the existing literature (e.g., Holcomb & Ponomarov, 2009; Peck & Christopher, 2004; Maklan & Jüttner, 2011.) furnished a resource model, particularly SCRE, but the principles of resource quantification for SCRE are until now non-existent (Halcomb & Ponomarov, 2009).

The fundamental assumption of this study is to enlarge the quantification aspect of dynamic capacities and elaborate on the circumstances of SCRE to fight obstacles arising from environmental unpredictability. This study proposes measuring and describing dynamic capacities concerning SCRE in conditions of responsive and proactive capabilities. Therefore, this work provided an essential extension of the dynamic capacity hypothesis.

2.2 Theory of Supply Chain Resilience

Resilience in the supply chain is defined as the capability to deal with uncertain and unexpected disruptive events. It also plays a role in recovering the disruption and quickly converting it to the original performance level or a new level necessary to maintain the supply chain's anticipated market, financial, and operating performance (Adobor, 2020). For the formation of resilience competencies and capability in the supply chain system, firms need to recognize and evaluate the nodes for risks, their strength of effects, their chances of occurrence, and how these uncertainties and risks can be identified (Chang et al., 2015; Dubey et al., 2018). Organizations adopt multiple techniques and strategies to maintain resilience in their supply chain systems. Through some supply chain systems, in the starting period of the COVID-19 pandemic, the buffers of inventory and capacity were recognized as a cause of resilience. On the other hand, other firms have used capacity of production that is underutilized for other products and medicines (Queiroz et al., 2020; Wong et al., 2020). Compared to a single source of supply, organizations with multi-sourcing strategies benefited from resilience (Sá et al., 2019).

2.3 Artificial Intelligence

Over the last two decades, several firms in the business world have been trying to adopt digitalization and advanced technologies in their processes. The application of Industry 4.0 has recently arisen in the business market (Wollschlaeger et al., 2017). Likewise, Artificial intelligence is the technique identified and recognized as a valuable technology that can enable adequate communication between machines and specific devices used in firm processes and functions (Dwivedi et al., 2019; Guzman & Lewis, 2020). As the supply chain system consists of various complex tasks, artificial intelligence has been utilized in firms to simplify operational activities by resolving issues and improving the speed and accuracy of handling large amounts of data and information (Schniederjans et al., 2020). The application of artificial intelligence is familiar in the business market, but its potential and capability have been recognized in the past few years (Huin et al., 2003). AI has the capability and competency to make agile, wise decisions in the SC system to avoid and resolve issues. Therefore, a very effective system of AI helps firms enhancement of service quality serving customers through safe and on-time deliveries of products and services (Schniederjans et al., 2020; Toorajipour et al., 2021; Hashmi & Mohd, 2020). The application of AI facilitates firms through computerized compliance that, in response, results in the minimization of cost and efficient performance of the firm through adding value to the network of the supply chain system (Treleaven & Batrinca, 2017). Artificial intelligence also has a positive influence on improving the predictive competencies that are necessary for estimating demand. Through AI bots, the engagement of customers as communication can be initialized. Through these bots, organizations can easily track the status of product deliveries and further help customers engage with a team of customer support (Huang & Rust, 2021). Through automation, AI applications help simplify the deadly tasks of warehouse operations. Well-known companies like Alibaba and Amazon are using it to increase productivity and improve the efficiency and effectiveness of their supply chain system (Ham, 2019). In the field of the supply chain, every minute has great importance, and the application of AI uses algorithms that efficiently support the supply chain system by minimizing cost and time laps by improving deliveries and routes (Wen et al., 2018).

2.4 Supply Chain Performance

In recent periods, a change has been observed in businesses to provide consumers with more choices by increasing the service offerings and products that generate further chances to overtake rivals (Um et al., 2017; Rashid & Amirah, 2017). Thus, practitioners and academics have focused on this trend to enhance the supply chain performance (SCP). In 2003, Yang and Burns asserted that collaboration among supply chain partners is essential for responding to changes in customer requirements. Additionally, the literature emphasizes the significance of understanding how dynamic or active supply chain partners are and examining how they strive for consistency (Schaltegger & Burritt, 2014; Rashid et al., 2019).

Moreover, a supply chain is an essential domain for any business firm to produce the element of value addition. The element of value is added only when an improvement is observed in the performance of SC processes. In the supply chain management system, value is generated through implementing coordination at a broader range (Rashid & Rasheed, 2022). While comparing the benefits of an enhancement in the performance of the supply chain, the researchers Salvador, Forza, and Rungtusanatham (2002) and Forza and Salvador (2001) claimed that the delivery process of products and level of production is influenced by increased labour cost and cost of raw material, increased manufacturing cost and also prolonged delivery of products and increase in level of inventory. The scholars Srinivasan, Mukherjee, and Gaur (2011) have delineated supply chain performance as the choice of specific functions crucial for the performance of the entire supply chain system. In the context of this particular research, supply chain performance is construed as the ability of the supply chain to carry out activities cost-effectively while simultaneously reducing costs to effectively meet customer needs (Green & Inman, 2005; Hashmi, 2022).

2.5 Hypothesis Development

2.5.1 Impact of artificial intelligence on supply chain performance

Grover et al. (2020) stated in the research study that artificial intelligence techniques enhance the supply chain system. Further researchers argued that it also plays a vital role in increasing the quality level of products, enhancing customer satisfaction, and playing a part in the design and development of firm products and processes. Applying artificial intelligence leads to enhanced operational performance in organizations compared to firm engagement. Furthermore, an integrated supply chain system driven by artificial intelligence, such as self-driving systems, has a significant positive impact on the logistics performance of the firm and its transportation functions. Previous research indicates that research frameworks based on artificial intelligence also contribute to decision-making in extensive distribution. Bottani et al. (2019) argue that implementing artificial intelligence results in a 56% reduction in out-of-stock situations. Additionally, scholars like Dubey et al. (2020) contend that using artificial intelligence techniques enhances an organization's overall performance.

According to the perspective of the Organization Information Processing Theory (OIPT), we propose that the adoption of artificial intelligence (AI) enables the supply chain to cultivate capabilities associated with information processing (Srinivasan & Swink, 2018). This allows them to interpret and extract knowledge from intricate information gathered from various sources, thereby reducing uncertainties in demand, supply availability, and capacities (Grover et al., 2020). In contrast, AI implementation is necessary for companies to maintain high levels of inventory or rely on the limited capabilities of human resources to establish a reactive supply chain, consequently impacting the firm's profitability and implementation speed (Dubey et al., 2020). Overall, such conceptions and evidence of the adoption of artificial intelligence can be considered as the tool that effectively improves the performance of the supply chain. Hence, a hypothesis proposed that:

H1(a): Artificial intelligence positively associated with supply chain performance

H1(b): Artificial intelligence has a positive indirect effect on supply chain collaboration.

H1(c): Artificial intelligence has a positive indirect effect on supply chain performance.

2.5.2 Impact of artificial intelligence on supply chain resilience

The field of supply chain management is considered the most challenging domain that emphasizes interaction between different departments of the firm, such as production, logistics and marketing. Thus, success in the supply chain system mainly relies on the success of overall business sectors as the business practices are shifting continuously toward the lean practices and JIT phenomenon, so various organizations are implementing this philosophy in logistics, operations and other globalized events such that numerous natural tragedies and unstable political environment, etc. To mitigate these challenges and issues, supply chains implement the concept of supply chain resilience in their systems to effectively deal with uncertain conditions (Hashmi, 2023).

Artificial intelligence technology was introduced in previous years, which proved valuable and essential for supply chain systems. The technique of artificial intelligence is explained as the capability of computers to freely and self-sufficiently resolve issues that they have yet to plan to address openly. According to previous research studies, using AI techniques will boost the economy to around 13 trillion by 2030 and effectively boost the world's GDP by about 1.2% each year. For several supply chain operations, practitioners used AI techniques in their firms. Most notably, it facilitates organizations by making practical decisions. With time, the AI technique is used for inventory management, demand forecasting, risk management, and sustainable SCM. In addition, the researcher further explained that the tool of artificial intelligence also plays a vital role in uncertainty and disruption like COVID-19 (Lai et al., 2020).

In forecasting and projection, Artificial Intelligence is used effectively and efficiently. Organizations have a long-lasting wish to maintain both the demand and the supply. As artificial intelligence (AI) predicts the data and automatically analyzes or processes the data or situation, a reliable and exact forecasting demand that the AI delivers. AI permits organizations to enhance their validation in processing orders and purchases and minimize costs related to supply chain administration, warehousing, transportation, etc. Additionally, it recognises the configuration and trends which assist in designing superior strategies related to retailing and manufacturing, for instance, most businesses use this tool in many ways, such as keeping or stocking the specific amount of a particular product that they will sell out and also reducing the waste. Artificial intelligence has permitted manufacturers to incorporate in production as well as client feedback to improve product design in real-time. Kraus et al. (2020) contend that tools based on artificial intelligence offer unparalleled accountability within the supply chain. AI facilitates rapid growth by improving engineering efficiency, preventing errors, reducing development phases, enhancing safety through automatic identification of risky activities, lowering inventory costs through adequate supply and demand planning, boosting revenue through increased sales rates leading to price optimization, and various other advantages (Patel et al., 2018). Consequently, this research posits the following hypothesis:

H2(a): Artificial intelligence positively influences Supply chain resilience

H2(b): Artificial intelligence has a positive indirect effect on supply chain resilience.

2.5.3 Artificial intelligence & adaptive capabilities

The existing literature of previous research studies has highlighted the importance of information and knowledge about the external factors of business firms. They believed it is essential to have enough know-how and understanding about the external environment to efficiently compete with the rivalries that firms face in the form of competitive business firms. For the successful survival of business firms, it is vital to have competitive capabilities to efficiently compete in the market by achieving competitive advantage. Adaptive capabilities are the central concept that organizations can adopt to become competitive in the market to make firm processes more resilient and competent (Scholten et al., 2019). According to researcher Dovers and Handmer (1992), adaptive capabilities include the element of stability, transformability, flexibility and persistence that mainly relates to the capability of an organization to accept the unstoppable transformation and organize or arrange all the resources for adjusting to the new situation and fulfilling updated requirements. Earlier research studies like Leitao (2009) clarify that artificial intelligence is a well-organized way of regenerating the element additively through learning and understanding the external atmosphere. In that way, they form a more systemized, adaptive, flexible and reconfigurable complex system at a higher level. Moreover, the researcher Macías-Escrivá et al. (2013) stated that artificial intelligence is a facilitating way to support adaptive system's new generations of advancement. Therefore, we hypothesize that.

H3: Artificial intelligence positively associated with Adaptive capabilities

2.5.4 Adaptive capabilities and supply chain resilience

The adaptive capability of a firm is defined as the maximum speed at which it can change its suggested portfolio. The maximum speed of change driven by the firm's adaptive capacity might differ from the noticeable speed of change. Firm capability refers to an organization's capacity to carry out specific tasks and responsibilities (Eshima & Anderson, 2017). Scholars and practitioners have associated adaptive capabilities with agility and flexibility (Appelbaum et al., 2017; Koçyiğit & Akkaya, 2020; Park & Park, 2021). Adaptive capability pertains to how quickly a firm can adjust its proposed portfolio to align with environmental changes.

Supply chain systems must enhance their capacity by implementing adaptive strategies to uphold environmental resilience. Implementing adaptive strategies provides a framework for learning and comprehending a system in a way that effectively aids the firm in improving its capacity to identify and mitigate uncertain and unforeseen situations (Alzoubi & Yanamandra, 2020). Adaptive management strategies aim to cultivate the ability to restructure the system in response to disruptive conditions (Um et al., 2017). The essential part of managing adaptive capabilities involves a frequent process of making decisions built to recognize and minimize uncertain and surprise events (Eshima & Anderson, 2017).

The researchers Scholten et al. (2019) claimed in their studies that the supply chain's resilience is relatively based on adaptive capabilities. It reduces the influence of unpredicted happenings by the preemptive recognition of strategies that allow the SC to adapt to the recovering after-effects and improve the level of prior situations. The researcher Li et al. (2020) examine that adaptive responses and planning are dynamic factors in developing resilience in the supply chain, which assists, according to the urban perspective, with any uncertain condition. Moreover, researchers such as Kochan and Nowicki (2018) in his study support the positive influence of adaptive capabilities in developing resilience in the supply chain by reducing the possibilities of challenging unscheduled events and also responding through preemptive plans in order to overcome the shock and reconstruct the state of the operations that is vigorous in the SC.

H4(a): Adaptive capabilities positively associated with supply chain resilience

H4(b): Adaptive capability has a positive indirect effect on supply chain performance.

H4(c): Adaptive capability has a positive indirect effect on supply chain resilience.

2.5.5 Adaptive capabilities and supply chain collaboration

In the literature of previous research studies, it is simplified that to perform competitively in the business world; firms must have enough knowledge and information about innovations and the external business atmosphere. An open innovation-driven adaptive capacity is a central conception that clarifies that an organization adapts strategies and other related things to compete in the market. The literature of earlier studies highlights the adaptive capabilities and collaboration of SC as the most influential elements required to build supply chain resilience (Chowdhury et al., 2019). Therefore, in this research study, adaptive capacity and SC collaboration are used as factors that enable SC resilience driven by the capabilities of artificial intelligence. By following this literature, we proposed that:

H5: Adaptive capabilities positively associated with supply chain collaboration

2.5.6 Supply chain collaboration and supply chain resilience

Collaboration is defined as the ability to work effectively with other organisations. It also acts as a method and tool for developing the capacity of the supply chain for regeneration and growth (Tarigan et al., 2021). The concept of collaboration enables the supply chain members to perform their tasks effectively. Also, it helps the firm efficiently deal with problems that it cannot handle when operating alone in the business market (Ho et al., 2019). The practice of collaboration builds an adaptive capacity in the supply chain system. It facilitates the firm through the creation and transfer of information throughout the supply chain system that enables the firm and its members to support each other while facing any disruptive situation (Basheer et al., 2019; de Sousa Jabbour et al., 2020). It also helps avoid disruptive situations and other issues through effective information sharing, using the strategy of mutual decision-making, arrangement of incentives, and collaborative communication (Duong & Chong, 2020).

Collaboration is when multiple individuals and departments work collectively to achieve a common goal. In supply chain management, it is crucial to coordinate and align the activities, work routines, and processes of individual organizations correspondingly to fully reap the benefits of collaboration (Alzoubi et al., 2020). Mainly, when addressing instances of disturbance and disruption, achieving resilience in the supply chain system is unattainable unless firms collaborate effectively, dynamically and synergistically to respond efficiently (Al-Doori, 2019; Jadhav et al., 2019; K.-H. Um & Oh, 2020). This statement underscores the vital role of collaboration in attaining resilience in the supply chain. Therefore, it is hypothesized that:

H6: Supply chain collaboration positively influences supply chain resilience

2.5.7 Supply chain collaboration and supply chain performance

In earlier research studies, the researchers Alzoubi et al. (2020) explained that the concept of collaboration in the supply chain has been considered a priority in many manufacturing firms operating worldwide. In the literature of previous studies, it is mentioned that the SC collaboration has many benefits provided to the firm in the form of minimization of cost, increase in profitability, controlling inventory level and exact estimation or forecast of demand and supply (Al-Doori, 2019). Moreover, collaboration in the supply chain plays a significant and positive role in enhancing supply chain performance. The researcher (Jain et al., 2017) agree and added his statement that integration and collaboration in processes and activities of the supply chain generate benefits that include lessening lead time, minimising the bullwhip effect, forming distinctive and unique capabilities, enhancing the level of flexibility, increase the satisfaction level of customer, enhance profitability and market share of the firm. However, many organisations genuinely realized the need for collaboration among SC members (Agyabeng-Mensah et al., 2020). Many firms fail to build collaboration among SC members because of unwillingness to share quality information but apply effort and make heavy investments (Ali & Haseeb, 2019). This kind of resistance destroys and minimizes the level of trust and commitment that is an essential part of collaboration in the supply chain field and SC's performance. This situation shows and highlights the importance of commitment and trust to enhance the performance of the supply chain and develop the element of collaboration in SC (Wang & Hu, 2017; Rashid & Rasheed, 2023). According to the perspective of small and medium enterprises, the collaboration factor also positively impacts the supply chain's performance. Thus, we propose a hypothesis that.

H7(a): Supply chain collaboration positively influences supply chain performance

H7(b): Supply chain collaboration has a positive indirect effect on supply chain performance.

2.5.8 Supply chain resilience and supply chain performance

A supply chain network with an element of resilience in its system allows it to enhance the capabilities of an organization to face disruptive situations. A resilient supply chain network also help firms to respond to disruptions and recover to normal condition quickly, ultimately helping firm enhance their performance (Adobor, 2020; Scholten et al., 2019). It is clear from the existing literature that the firm that takes more time to respond to disruptions incurs significant damage that results in a low performance level. Moreover, in another research study, the phenomenon of resilience related to the concept of services in 3PL firms, the research found a positive impact on the performance of services. It can be claimed that the organization with more resilience in its supply chain system performs better in detecting the principal risks and threats that a firm faces in the market.

Moreover, it is found in many studies that the resilience factor in the supply chain is positively associated with a high level of firm performance that occurs in terms of achieving competitive advantages and enhanced profitability. Through resilience, organizations also receive an element of customer satisfaction that they consider important performance outcomes (Govindan et al., 2013). Furthermore, the ability of a firm's supply chain system to bounce back from disruptive events serves as a valuable capability and competitive advantage, allowing the company to recover from challenging situations (Gligor et al., 2019; Rashid et al., 2023b). Consequently, numerous earlier research investigations assert that resilience in the supply chain significantly enhances overall supply chain performance (Gölgeci & Kuivalainen, 2019). Building upon this understanding, hypotheses were developed, which are as follows:

H8: Supply chain resilience positively influences supply chain performance

3. Methodology

The research approach states that the plan and procedure of a research study will be conducted or explored (Rashid et al., 2020). There are two research approaches: quantitative and qualitative (Khan et al., 2023), while the third approach combines both approaches. The objective of the qualitative study is to discover new perceptions/theories, whereas, in the quantitative approach, the researcher will work with existing theories and test these theories to test the relationship among various variables. In qualitative studies, the data is collected by interviews, while in quantitative studies, experiments, surveys, questionnaires, and observations can collect data. Moreover, in quantitative study, data is collected in numeric form.

The current investigation relied on established theories to examine the connection between various variables, with data collection conducted through a structured questionnaire and survey technique. Consequently, this study opted for a quantitative research approach, aligning to test existing theories, as emphasized by Rashid et al. (2022a).

Data collection sources highlight the nature of data, which means how the researchers gather data for research. These data collection sources are divided into two major types: primary sources and secondary sources of data collection (Rashid et al., 2022b). The primary data is the newly collected data, while the secondary data has already been recorded for other purposes. Further, primary data can be collected through experiments, observations, questionnaires, surveys and interviews with individual respondents. On the other hand, secondary sources include books, journals, annual reports, and other internet sources. In this study, the data was collected using primary sources, and a survey questionnaire was used to gather the data.

3.1 Population and Target Population

Rashid et al. (2021) stated that the research study population referred to a whole pool of individuals related to a specific sector. Asiamah et al. (2017) stated that the population has three types: general population, target population and accessible population. The entire pool of individuals related to the selected sector/industry is termed the general population. In contrast, the targeted population states those individuals who are most related to the research objective. The researcher also describes the accessible population, which means those individuals who can easily participate in research by adding their responses.

In the current study, the general population contains individuals related to a selected sector, i.e., employees of manufacturing firms. This general population has narrowed down to a target population, which is closely related to research objectives, i.e. in the current study, employees are related to the supply chain department in manufacturing firms. Moreover, the accessible population contains the reachable and feasible individuals who will participate in this study, including the pharmaceutical sector employees.

3.2 Sample and Sampling

Hashmi et al. (2021a) stated that collecting data from the whole target population is not possible and feasible because it takes too much time and money. So, to cope with this problem, the author suggested taking a sample from the target population that represents the whole population.

However, there are two primary techniques for sampling: probability sampling and non-probability sampling (Khan et al., 2021; 2022b). Probability sampling is based on the pre-defined chance of choosing respondents for the sample. In contrast, in non-probability sampling, all individuals have an equal chance to be part of the sample (Hashmi et al., 2021b). The probability sampling technique has further types, which include simple random sampling, stratified random sampling, cluster sampling and systematic sampling. On the other hand, non-probability sampling also contains several types: convenience, snowball, quota, and purposive.

In the current study, all respondents have an equal chance of participating in the research, and the researcher also still needs to fix the chances of selecting a sample size, so non-probability sampling was used to take a sample. Moreover, non-probability sampling is further divided into four types: quota sampling, snowball sampling, convenient sampling, and judgmental sampling. In the present study, non-probability sampling was used, and convenient sampling was used for the sample (Khan et al., 2022a).

The sample size represents the count of individuals contributing responses during the data collection phase (Hashmi et al., 2020a). Emphasizing the importance of reliability, it was highlighted that the sample size should be determined through credible sources to enhance result accuracy (Hair et al., 2019). This investigation determined the sample size using G*power software, which computes the sample size based on a suitable statistical model and the number of predictors (Faul et al., 2009). The projected sample size for this study was identified as 129 respondents.

The statistical analysis applied in this study includes descriptive statistics to check the univariate normality, reliability analysis to test the internal consistency of data and bivariate correlation analysis will be applied used to examine the multicollinearity issue. The regression analysis will test the proposed hypothesis (Rashid, 2016; Hashmi et al., 2020b).

3.3 Instrument

A structured closed-ended questionnaire served as the tool for gathering data, incorporating constructs adapted from prior research studies. These constructs encompassed artificial intelligence (AI), adaptive capability (AC), supply chain collaboration (SCC), supply chain resilience (SCR), and supply chain performance (SCP). Table 1 below provides an overview of these constructs and their respective references.

Table 1: Instrument

Constructs	Items	Sources
Artificial intelligence	5	(Dubey et al., 2020)
Adaptive capability Supply chain	3	(Tarafdar & Qrunfleh, 2016)
collaboration	3	(Dubey et al., 2020)
Supply chain resilience	5	(Yu et al., 2019)
Supply chain performance	4	(Belhadi et al., 2021; Srinivasan & Swink, 2018)

Source: Literature

4.1 Demographic Profile of Participant

The demographic profile of the respondents is shown in given below table 2:

Table 2: Demographic profile of the participant

Demographic variable	Category	Frequency	Percentage
Gender	Male	174	84.5
	Female	32	15.5
Age	Less than 25 years	36	17.5
	25- 30 years	128	62.1
	36-40 years	42	20.4
	Above 40 years	0	0
Experience	less than three years	93	45.1
	3 to 6 years	89	43.2

	7 to 10 years	24	11.7
	above ten years	0	0
Designation	Executive	96	46.6
	Assistant Manager	82	39.8
	Manager	28	13.6
	Senior Manager	0	0
	Director	0	0
Income	25,000- 40,000	85	41.3
	41,000- 70,000	64	31.1
	71,000- 100,000	48	23.3
	Above 100,000	9	4.4
Education	Diploma	14	6.8
	Intermediate or less	55	26.7
	Graduation	53	25.7
	Masters	8	3.9
	M Phil/PhD	76	36.9

Source: SPSS output

4.2 Descriptive Statistics

Descriptive statistics were employed to assess the normality of the data, encompassing measures such as the mean, standard deviation, skewness, and kurtosis. According to Hair et al. (2019), achieving univariate normality entails ensuring that skewness and kurtosis values fall within the range of +2.5. Table 3 below provides an overview of the descriptive statistics:

Table 2: Descriptive statistics

Construct	Std. Dev.	Mean	Skewness	Kurtosis
Artificial intelligence	3.53	0.75	-.403	-.069
Adaptive capability	3.60	0.72	-.464	.364
Supply chain collaboration	3.60	0.70	-.773	1.271
Supply chain resilience	3.54	0.74	-.738	.217
Supply chain performance	3.53	0.78	-.936	1.233

Source: SPSS output

The calculated outcomes presented in the table above (Ref. table 2) affirm that the construction supply chain performance (SCP) (Mean=3.53, S.D=0.78) has the maximum skewness (sk=0.936). In contrast, the construct Artificial Intelligence (AI) (Mean=0.403, S.D=0.75) has the least skewness (sk= 0.403). Besides this, the construct Supply chain collaboration (SCC) (Mean=3.60, S.D=0.70) has the maximum kurtosis (k=1.271), whereas the construct Artificial intelligence (AI) (Mean=0.403, S.D=0.75) has the least kurtosis (k=0.069). Since none of these results are out of range (i.e. ±2.5), the univariate normality existed in the collected data.

4.3 Reliability Analysis

Hair et al. (2019) noted the potential for errors in responses gathered from respondents and the data collection process. A reliability analysis was conducted to ensure internal consistency in the collected data. It was determined that the reliability value should be a minimum of 0.70 or higher (Das et al., 2021; Haque et al., 2021). Table 4 below presents the results of the reliability analysis:

Table 3: Reliability analysis

Construct	α	Mean	Standard Deviation
Artificial intelligence	.740	3.53	0.75
Adaptive capability	.784	3.60	0.72
Supply chain collaboration	.759	3.60	0.70
Supply chain resilience	.725	3.54	0.74
Supply chain performance	.764	3.53	0.78

Source: SPSS output

The results presented in the above table (Ref. Table 3) illustrate that the construct maximum reliability value (Alpha = 0.784) is for measurement scale Adaptive capability (AC) (Mean =3.60, S.D=0.72). In contrast, the least reliable (Alpha =0.725) is for constructing Supply chain resilience

(SCR) (Mean=3.54, S.D=0.74). Since these outcomes illustrate that all measurement scales have at least 0.70 reliability, all adapted constructs used in this study are reliable for this study (Alrazehi et al., 2021).

4.4 Correlation Analysis

To test the multicollinearity issue, correlation analysis was determined to emphasize the strength of association among each pair of variables. According to Rashid (2016), the minimum correlation among each pair of variables should be at least $\pm$0.30, and the maximum correlation among each pair of variables should be at most $\pm$0.90. The mention Table 5 below indicates the consolidated outcomes for bivariate correlation analysis:

Table 4: Bivariate correlation

Construct	T_AI	T_AC	T_SCC	T_SCR	T_SCP
Artificial intelligence	1				
Adaptive capability	.436**	1			
Supply chain collaboration	.436**	.408**	1		
Supply chain resilience	.535**	.353**	.514**	1	
Supply chain performance	.447**	.303**	.360**	.562**	1

** Correlation is significant at the 0.01 level (2-tailed).

Source: SPSS output

Based on the computed results presented in the above table (refer to Table 4), it is evident that the most robust relationship (r=0.562) exists between Supply Chain Performance (SCP) (Mean=3.53, S.D=0.78) and Supply Chain Resilience (SCR) (Mean=3.54, S.D=0.74). On the other hand, the weakest correlation (r=0.303) is observed between Supply Chain Performance (SCP) (Mean=3.53, S.D=0.78) and Adaptive Capability (AC) (Mean=3.60, S.D=0.72). These values indicate that the association between each pair of constructs falls within the range of +0.30 to +0.90. Consequently, these findings affirm no multicollinearity issue with the constructs employed in the present study (Rasheed & Rashid, 2023).

4.5 Construct Validity

The application of convergent and discriminant validity tested the construct validity. The results are discussed in given below section:

4.5.1 Convergent validity

Convergent validity was applied to examine the inter-item relationship. The acceptability criteria for convergent validity include composite reliability (Hair et al., 2019), which should not be less than 0.70, and the loading factor should not be less than 0.40. Moreover, the Average Variance Extracted (AVE) for each construct must not beat at least 0.50, as Fornell and Larcker (1981) recommended. The results for the three criteria mentioned above are succinctly presented in the following Table 6:

Table 5: Convergent validity

Construct	Items	Factor loading	AVE	Composite reliability(CR)
Adaptive capability	AC1	0.770	0.563	0.795
	AC2	0.746		
	AC3	0.736		
Artificial intelligence	AI1	0.639	0.512	0.839
	AI2	0.687		
	AI3	0.776		
	AI4	0.761		
	AI5	0.705		
Supply chain collaboration	SCC1	0.700	0.542	0.779

	SCC2	0.709		
	SCC3	0.794		
Supply chain performance	SCP1	0.760	0.582	0.848
	SCP2	0.777		
	SCP3	0.717		
	SCP4	0.796		
Supply chain resilience	SCR2	0.727	0.544	0.826
	SCR3	0.822		
	SCR4	0.720		
	SCR5	0.672		

Source: SmartPLS output

The results in table 6 indicate that the factor loading of all items is at least 0.40, and composite reliability (CR) for adaptive capability, artificial intelligence, supply chain collaboration, supply chain performance, and supply chain resilience is not less than 0.70. Furthermore, the Ave for all constructs is also at least 0.50. So, the convergent validity was established for all constructs.

4.5.2 Discriminant validity

Discriminant validity was evaluated to assess the differentiation among all constructs employed in this study, using the approach proposed by Fornell and Larcker (1981). According to this method, each construct's square root of the Average Variance Extracted (AVE) should exceed the correlation between each pair of variables. The summarized results for discriminant validity are presented in Table 7 below:

Table 6: Discriminant validity

Construct	T_AC	T_AI	T_SCC	T_SCP	T_SCR
Adaptive capability	0.751				
Artificial intelligence	0.445	0.715			
Supply chain collaboration	0.406	0.443	0.736		
Supply chain performance	0.307	0.468	0.366	0.763	
Supply chain resilience	0.331	0.545	0.487	0.545	0.737

Source: SmartPLS output

The table mentioned above 7 illustrates the discriminant validity in which the square root of AVE is presented on the diagonal of the above table. The outcomes show that the square root AVEs for AC, AI, SCC, SCP and SCR are higher than the correlation value of each construct pair. Thus, the acceptable criteria for discriminant validity have been fulfilled.

Moreover, the Heterotrait-Monotrait Ratio (HTMT) was also applied to analyze the discriminant validity of the construct. This method is the updated approach of Fornell and Larcker (1981) in PLS-SEM to examine the discriminant validity of the construct. The acceptance criteria stated that the value of HTMT among each pair of constructs should be less than 1.00, not greater than 0.90, and also lower than 0.85. Thus, the outcomes presented in Table 08 below show that all HTMT values are not greater than one, so it fulfilled the discriminant validity standard.

Table 8: Heterotrait-monotrait Ratio

Construct	T_AC	T_AI	T_SCC	T_SCP	T_SCR
Adaptive capability					
Artificial intelligence	0.638				
Supply chain collaboration	0.690	0.658			
Supply chain performance	0.443	0.587	0.542		
Supply chain resilience	0.501	0.706	0.750	0.721	

Source: SmartPLS output

4.6 Testing Overall Model SEM

The proposed tested model has three independent variables, which are Adaptive capability (AC), Artificial intelligence (AI), and Supply chain collaboration (SCC); one dependent variable is Supply chain performance (SCP). However, one mediating variable is supply chain resilience (SCR). The output of the estimated path model is presented in given below figure 2:

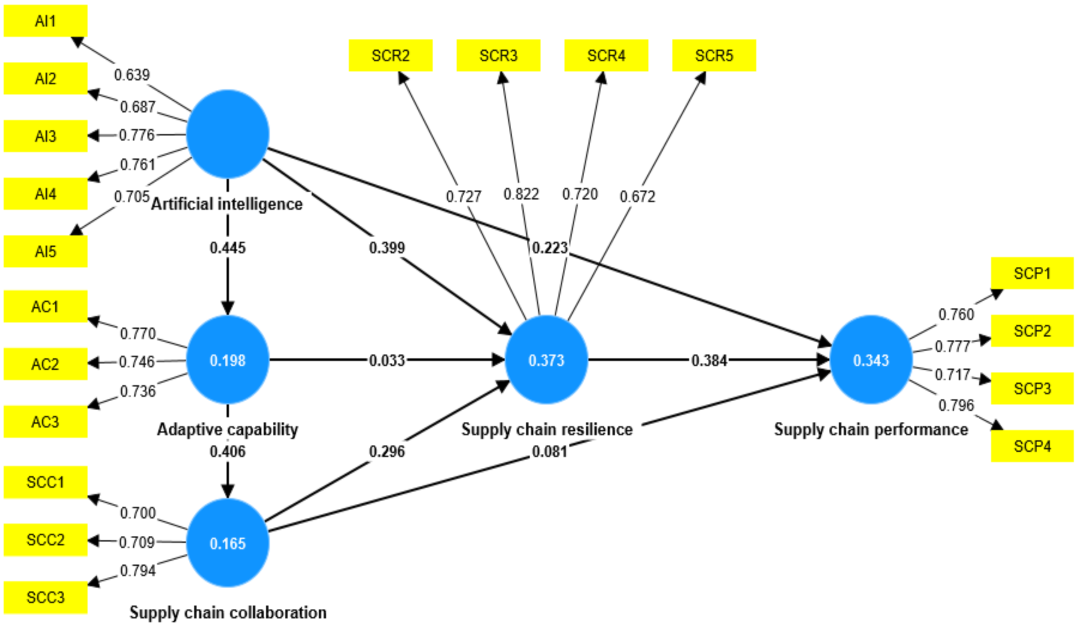

Figure 2: SEM path diagram

Source: SmartPLS graphics

Structural educational modeling (SEM) was applied to test the proposed hypothesis of this study. The results of SEM were based on the Beta, p-values of the hypothesis path and confidence interval (LL and LU) (Hair et al., 2019). The confidence interval (CI) illustrates the values of the upper level (UL) and lower level (LL), but it is required that the value should not overlap to zero among each level (Hashmi et al., 2021). Before moving forward to overall model testing, it should be confirmed that all the adapted constructs have no issue with multicollinearity. Hair Jr et al. (2016) state that if the correlation among each pair of variables is not less than 0.30 and not greater than 0.90, it can be safely assumed that variables have no issue with multicollinearity. Thus, it was safely assumed that the path coefficient analysis and hypothesis testing could proceed.

The bootstrapping with 500 resamples was applied to test the hypothesis. The calculated results presented in give below table 9, AC→SCR (Beta =0.406, $p<0.000$, t=6.473: LL=0.284, UL=0.531), AI→AC (Beta =0.445, $p<0.000$, t=7.948, LL=0.340, UL=0. 558), AI→SCP (Beta =0. 223, $p<0.014$, t=2.454, LL=0. 043, UL=0. 395), AI→SCR (Beta =0. 399, $p<0.000$, t=5.903, LL=0. 261, UL=0. 528), SCC→SCR (Beta =0. 296, $p<0.000$, t=4.475, LL=0. 166, UL=0. 553) SCR→SCP (Beta =0. 384, $p<0.000$, t=4.314, LL=0. 207, UL=0. 553). However, hypothesis (H1(a), H3, H4(a), H5, H7(a) and H8) are retained and the results are supported.

Table 9: Results of the structural model

Path	*Beta*	*T statistics*	*p-value*	*LL*	*UL*	*Remarks*
Adaptive capability -> Supply chain collaboration	*0.406*	*6.473*	*0.000*	*0.284*	*0.531*	*Yes*
Adaptive capability -> Supply chain resilience	*0.033*	*0.460*	*0.646*	*-0.106*	*0.180*	*No*
Artificial intelligence -> Adaptive capability	*0.445*	*7.948*	*0.000*	*0.340*	*0.558*	*Yes*
Artificial intelligence -> Supply chain performance	*0.223*	*2.454*	*0.014*	*0.043*	*0.395*	*Yes*
Artificial intelligence -> Supply chain resilience	*0.399*	*5.903*	*0.000*	*0.261*	*0.528*	*Yes*
Supply chain collaboration -> Supply chain performance	*0.081*	*0.975*	*0.330*	*-0.075*	*0.253*	*No*
Supply chain collaboration -> Supply chain resilience	*0.296*	*4.475*	*0.000*	*0.166*	*0.430*	*Yes*
Supply chain resilience -> Supply chain performance	*0.384*	*4.314*	*0.000*	*0.207*	*0.553*	*Yes*

Source: SmartPLS output

The bootstrapping with 500 resamples was applied to test the hypothesis for indirect effect among dependent and independent variables. The calculated results presented in give below table 10, AC→SCR (Beta =0.120, p<0.000, t=1.935: LL=0.008, UL=0.194), AC→SCR (Beta =0.120, p<0.001, t=2.262, LL=0.059, UL=0. 203), AI→SCC (Beta =0. 181, p<0.000, t=4.238, LL=0. 110, UL=0. 278), AI→SCP (Beta =0. 194, p<0.000, t=4.494, LL=0. 119, UL=0. 228), AI→SCR (Beta =0. 068, p<0.046, t=1.992, LL=0.008, UL=0. 144) SCC→SCP (Beta =0.114, p<0.001, t=3.291, LL=0.053, UL=0.183). However, hypothesis (H4(b), H1(c), H1(c), H5, H7(a), H2(b) and H7(b)) are retained and the results are supported.

Table 10: Indirect effects

Path	Beta	T statistics	*p*-value	LL	UL	Remarks
Adaptive capability -> Supply chain performance	0.092	1.935	0.053	0.008	0.194	No
Adaptive capability -> Supply chain resilience	0.120	3.262	0.001	0.059	0.203	Yes
Artificial intelligence -> Supply chain collaboration	0.181	4.238	0.000	0.110	0.278	Yes
Artificial intelligence -> Supply chain performance	0.194	4.494	0.000	0.119	0.288	Yes
Artificial intelligence -> Supply chain resilience	0.068	1.992	0.046	0.008	0.144	Yes
Supply chain collaboration -> Supply chain performance	0.114	3.291	0.001	0.053	0.186	Yes

Source: SmartPLS output

5. Summary and Conclusion

5.1 Conclusion

The primary objective of this research study is to explore the factors influencing supply chain resilience to improve supply chain performance, mediated through the impact of supply chain resilience. The study focuses on the manufacturing industry in Karachi, Pakistan, and is rooted in existing theories of supply chain resilience. It investigates the effects of specific factors—such as artificial intelligence, adaptive capabilities, and supply chain collaboration—on supply chain resilience. Additionally, the research model examines how supply chain resilience influences overall supply chain performance.

Quantitative research methods were employed for this study, and data were collected through a questionnaire. Due to practical constraints, a sample size of 129 respondents from the target population was calculated using G*power software. A total of 206 responses were obtained by distributing the developed questionnaire within the target population. The collected data were analyzed using structural equation modeling with smart PLS4 software, leading to the overall findings of the research.

The analysis revealed that all proposed hypotheses, except for hypotheses two and six, demonstrated positive and significant outcomes. The results concluded that artificial intelligence, adaptive capability, and supply chain collaboration positively and significantly influence supply chain resilience and performance. Furthermore, the study affirmed that supply chain resilience positively impacts supply chain performance. Consequently, organizational and supply chain performance can be enhanced by adopting supply chain resilience and other dynamic capacities within the organization.

5.2 Discussion

All the proposed hypotheses were consistent with existing studies as all the hypotheses were retained except for hypotheses 2 and 6. The given below sections discuss the found outcomes in the comparison with existing information present in the literature:

The research hypothesis stating that "Artificial intelligence is positively associated with supply chain resilience" was upheld, aligning with the findings for research question one: Does artificial intelligence have a relationship with supply chain resilience, as corroborated by existing literature? For example, researcher Kraus et al. (2020) emphasize that artificial intelligence tools enhance supply chain accountability. AI facilitates rapid growth by improving engineering efficiency, preventing errors, reducing development phases, automatically identifying risky activities to enhance safety, lowering inventory costs through adequate supply and demand planning, and boosting revenue through optimized sales rates and pricing strategies (Patel et al., 2018).

Similarly, the research hypothesis asserting that "Artificial intelligence is positively associated with supply chain performance" was also upheld, aligning with the findings for research question two: Does artificial intelligence have a relationship with supply chain performance, as supported by existing literature? According to the Organization Information Processing Theory (OIPT) perspective, the implementation of artificial intelligence (AI) enables the development of information processing capabilities within the supply chain (Srinivasan & Swink, 2018). This allows for interpreting and extracting knowledge from complex information, reducing uncertainties in demand, supply availability, and capacities (Grover et al., 2020). Without AI implementation, firms may maintain high inventory levels or rely on limited human capabilities, resulting in a reactive supply chain that negatively impacts profitability and implementation speed (Dubey et al., 2020). In summary, adopting artificial intelligence is a tool that effectively enhances supply chain performance.

The research hypothesis “Artificial intelligence positively associated with adaptive capabilities” was retained and answered to research question three: Does artificial intelligence have a relationship with adaptive capabilities? Does it match with existing literature? For instance, Earlier research studies like Leitao (2009) clarify that the application of artificial intelligence constitutes a well-organized way of regenerating the element of additivity through learning and understanding the external atmosphere. In that way, they form a complex system that is more systemized, adaptive, flexible, and reconfigurable at a higher level. Moreover, the researcher Macías-Escrivá et al. (2013) stated that artificial intelligence is a facilitating way to support adaptive system's new generations of advancement.

The research hypothesis stating that "Adaptive capabilities are positively associated with supply chain collaboration" was affirmed, aligning with the findings for research question five: Does adaptive capabilities have a relationship with supply chain collaboration, as supported by existing literature? Earlier studies underscore the significance of adaptive capabilities and supply chain collaboration as pivotal elements for building supply chain resilience (Scholten et al., 2019; Chowdhury et al., 2019; Jain et al., 2017). Consequently, in this research study, adaptive capacity and supply chain collaboration are considered factors contributing to supply chain resilience, propelled by the capabilities of artificial intelligence.

Similarly, the research hypothesis positing that "Supply chain collaboration is positively associated with supply chain resilience" was upheld, aligning with the findings for research question six: Does supply chain collaboration have a relationship with supply chain resilience, as substantiated by existing literature? In addressing disturbances and disruptions, achieving resilience in the supply chain system necessitates effective collaboration among firms dynamically and synergistically for an efficient response (Jüttner & Maklan, 2011; Ponomarov & Holcomb, 2009). This assertion underscores the critical importance of collaboration in attaining resilience in the supply chain.

Furthermore, the research hypothesis asserting that "Supply chain resilience is positively associated with supply chain performance" was supported, aligning with the findings for research question eight: Does supply chain resilience have a relationship with supply chain performance, as confirmed by existing literature? Resilience contributes to customer satisfaction, is considered a vital performance outcome, and a capability and competitive advantage enabling firms to recover from disruptive situations (Govindan et al., 2013; Gligor et al., 2019). Various previous research studies emphasize the significant role of resilience in the supply chain in enhancing overall supply chain performance (Gölgeci & Kuivalainen, 2019).

5.3 Implications

5.3.1 Practical implications

This research study offers valuable insights to practitioners and managers in the manufacturing industry, aiding them in enhancing their supply chain resilience. The concept of supply chain resilience is receiving a high level of attention and becoming famous among managers of the firm because the concept of a resilient supply chain increases the capability and feasibility of SC. Resilience in the supply chain also enables the SC partners to achieve their goals and increase their competitiveness and benefits. The essential practical implication of this research is that it will help in emerging vital resources and trajectory views for managing strategies that are the main factors of resilient SC. Through this, associated parties can widely concentrate on those practices that may increase the supply chain performance of an organization.

5.3.2 Theoretical implications

This specific research study plays a significant role in the literature by shedding light on the concepts of supply chain resilience and the supply chain performance of organizations. In particular, the study explores the factors influencing supply chain resilience, such as artificial intelligence, adaptive capability, and supply chain collaboration. The theoretical framework of the model can be extrapolated to other forms of inter-organizational relationships, expanding the understanding of resilience in the supply chain. Furthermore, the research contributes to the knowledge base by incorporating artificial intelligence, adaptive capability, and supply chain collaboration as independent variables affecting supply chain resilience. It emphasizes that enhancing the supply chain resilience system can improve performance.

5.4 Limitations and Recommendations

Several noteworthy limitations and recommendations warrant specific discussion in the context of this research study. The study faces various limitations, notably a need for more comprehensive literature to validate the content scales. The current study's primary focus is examining the impact of artificial intelligence, adaptive capability, and supply chain collaboration. Future research endeavours could explore variations among target segments, incorporating additional variables such as operating frontier, trajectory, and absorptive capacity. It is emphasized that obtaining meaningful outcomes would be contingent upon utilizing a substantial sample size.

For future research, enhanced content validation is imperative, and adopting the approach outlined by Moore and Benbasat (1991) would contribute to a more robust validation of content when combined. Additionally, upcoming studies on this topic could explore whether alternative variables impact the connections between artificial intelligence, adaptive capability, supply chain collaboration, and supply chain resilience's proactive and reactive dimensions. It is crucial and advisable for future research efforts to consider an expanded sample size.

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