An Analytical Study on Integrating Artificial Intelligence and Industry 4.0 Technologies for Supply Chain Resilience and Sustainability

Abstract:

This study examines how the adoption of AI-driven predictive analytics and Industry 4.0 (I4.0) technologies enhances supply chain resilience (SCR) and sustainable supply chain performance (SSCP) in the food manufacturing industry, with SCR serving as a mediating factor. Grounded in the Dynamic Capabilities perspective, the research employs a quantitative approach using data collected from 194 professionals working in the food manufacturing sector. Structural Equation Modeling (SEM) with SmartPLS 4.0 was employed to test the hypothesized relationships and assess both direct and mediating effects. The results reveal that AI-driven predictive analytics and I4.0 integration have a strong positive influence on both SCR and SSCP. Moreover, SCR plays a critical mediating role in linking technology adoption to sustainable supply chain performance, underscoring its strategic importance in driving sustainability transitions. The study contributes to the growing body of knowledge on the intersection of digital technologies, resilience, and sustainability, offering practical insights for organizations in developing economies seeking to leverage technological capabilities to achieve adaptability, competitiveness, and sustainable growth through the lens of dynamic capabilities.

Keywords: Artificial intelligence, Predictive analytics, Industry 4.0 technologies, Supply chain resilience, Sustainable performance , Dynamic capabilities.

Paper Type: Research Paper

1. Introduction

Global supply chains (GSCs) are currently more susceptible to systemic shocks caused by geopolitical crises, pandemic (Covid-19), climatic, and fluctuating demand. The recent crises have shown that efficiency-driven, globally spread supply networks are extremely vulnerable to cascading effects of risks, which has revived scholarly and policy attention to the concept of supply chain resilience (Baldwin & Freeman, 2022). Modern turbulence is characterized by structural uncertainty in interconnected global systems of production rather than short term shocks. As a result, organizations are no longer focusing on efficiency-driven models but instead, are transitioning to digitally enabled, resilient and sustainable supply chain structures.

Artificial intelligence (AI) -powered predictive analytics has become a highly important uncertainty management capability in this dynamic environment. Predictive analytics uses past and present data to predict the changes in demand, fluctuations in prices, and trends of disruptions, with the help of which informed and proactive decisions can be made (Iseri et al., 2025). As opposed to descriptive analytics, predictive models are more beneficial in increasing predictive ability as they convert information into a foresight which is actionable to enhance responsiveness and allocation of resources within supply circles. Empirical findings indicate that the performance of a supply chain, which is improved by big data analytics capabilities, is resilience-enhanced and innovatively enabled indirectly (Bahrami et al., 2022). On the same note, the mediating role of analytics capability has been demonstrated to exist between resilience and complexity of the supply chain (Iftikhar et al., 2023). These results demonstrate that analytics is not only an organizational capability that augments adaptive capacity in the face of uncertainty but also a technological instrument.

Along with the development of analytics, Industry 4.0 (I4.0) integration as the implementation of cyber-physical systems, Internet of Things (IoT), blockchain, digital twins, and intelligent automation has reorganized the supply chain operations. I4.0 allows visibility in real-time, coordination between organizations, and optimization of processes throughout the supply chains (Khan & Emon, 2025). In addition to operational efficiency, digital integration contributes to the sustainability goals by increasing transparency, minimizing waste, and promoting the use of the circular supply chain (Ghobakhloo, 2020; Lu et al., 2024). Nonetheless, although the previous research has investigated the direct influence of I4.0 on the performance of the supply chain (Mohaghar et al., 2026), scarce studies have investigated the interaction of digital infrastructure integration with analytics capability to enhance resilience mechanisms.

Resilience has been conceptualized in a progressively higher-order organizational capability that facilitates supply chains to anticipate, absorb, adjust to and overcome disruptions. Empirical research findings show that resilience mediates the correlation between supply chain integration and performance (Piprani et al., 2020), between the ability of big data analytics and performance outcomes (Bahrami et al., 2022). However, the existing literature studies analytics or Industry 4.0 as the independent variables with only a few studies incorporating the two terms in a cohesive theoretical framework to explain the way in which digital capabilities can change into sustainable performance through resilience.

Theoretically, dynamic capabilities view (DCV) can be used to study this mechanism. DCV is based on the idea that companies maintain competitive advantage through the creation of sensing, seizing and transforming capabilities to react to environmental turbulence (Gupta et al., 2020). In this context, AI-powered predictive analytics can be imagined as a sensing power that will improve environmental scanning and foresight, and Industry 4.0 integration can be seen as a transforming power, which allows reconfiguring processes and inter-organizational connections digitally (Teece et al., 1997a). In its turn, supply chain resilience demonstrates a higher-order dynamic capability that operationalizes sensing and converting into adaptive performance results.

The paper fills the previous gaps because two distinct dynamic capabilities between AI-based predictive analytics and Industry 4.0 integration are distinguished, supply chain resilience is a mediating variable between digitalization and sustainable performance, and the integrated model is tested in an empirical situation in an emerging economy. By so doing, it expands but not subjugates the dynamic capabilities perspective by contextualized empirical evidence. Based on these gaps, this study addresses the following research questions:

- **RQ1:** *How does the integration of AIDPA and I4.0 technologies jointly influence SCR and SSCP in the food manufacturing sector?*
- **RQ 2:** *To what extent does supply chain resilience mediate the relationship between AIDPA, I4.0 integration, and SSCP?*

This study answers these questions in such a manner that it has three implications on the literature. First, conceptually, it augments the dynamic capabilities perspective with predictive analytics via AI and Industry 4.0 integration as complementary digital capabilities to increase supply chain resilience. This study does not introduce a new theory, instead, promoting DCV by synthesizing empirically in a digital supply chain setup. Second, methodologically, it is a more detailed structural model that investigates mediation effect, which answers the calls to investigate resilience mechanisms more detailed in analytics studies (Iftikhar et al., 2023). Third, empirically, the results provide practical implications to decision-makers in emerging markets in that investments in predictive analytics and digital integration have the potential to increase the performance of resilience and long-term sustainability.

2. Literature Review: A Theory-Driven Systematic Synthesis

2.1 Systematic Review Protocol and Analytical Strategy

This paper uses a systematic literature review (SLR) to conduct a synthesis of available studies that have connected digital technologies and supply chain resilience (SCR) and sustainable supply chain performance (SSCP) to provide a sound theoretical basis of the present study. The method of systematic literature review is now a common practice in the research of supply chain and operations management to determine theoretical trends, conceptual gaps, and model configurations (Iftikhar et al., 2024; Núñez-Merino et al., 2020). Contrary to the narrative review, where the studies are frequently summarized in a descriptive way, the SLR approach allows developing a theory-oriented synthesis of constructs, relationships, and methods of analysis applicable to the research model.

The search of the literature was done on the basis of Scopus and Web of Science two of the best sources of the academic literature on operations and supply chain activities. Keywords were formulated depending on the core constructs of the study and had combinations of:

- Artificial intelligence-based predictive analytics.
- Big data analytics capability
- Industry 4.0 integration
- Digital supply chain
- Supply chain resilience
- Dynamic capabilities

The sustainable supply chain performance. The timeline of the review is 1997-2025 because there is a need to capture both the creation of the Dynamic Capabilities View (DCV) (Teece et al., 1997) and its further use in digitally enabled supply chains. In the search, 132 articles were first obtained. Upon eliminating duplicates and filtering abstracts related to the research topic on digital capabilities, resilience and sustainability results in supply chains, 52 peer-reviewed articles were left to be fully analyzed. In order to guarantee analytical rigor, all the studies were coded in a systematic way across six dimensions:

- Theoretical lens
- Digital capability under investigation.
- Supply chain resilience role.
- Model structure (direct vs mediated relationships)
- Empirical methodology
- Research setting (developed and emerging economies)

This analytical method provides the opportunity to identify theoretical trends, conceptual discontinuities, and gaps in the body of research to underpin the formulation of the current study.

2.2 Theoretical Foundations: Dynamic Capabilities

The theoretical base of the study of the way firms respond to technological disturbances and environmental turbulence is the Dynamic Capabilities View (DCV). Originally, DCV was theorized by (Teece et al., 1997) to say that organizations maintain competitive advantage not by their possession of valuable resources but as a result of their capabilities to reuse the resources in accordance with the evolving environments. (Teece, 2007) also explained the micro foundations of dynamic capabilities, pointing out three processes in the organization, namely:

- **Sensing**: detection of opportunities and threats on the external environment.
- **Seizing**: resources mobilization in order to seize opportunities.
- **Transforming (reconfiguring)**: constantly changing the operational capabilities.

The processes are especially applicable in digitally enabled supply chains whereby companies have to constantly read market signals, react to shocks, and re-architecture operational systems. The recent supply chain research has started to use DCV as a way of explaining the impact of digital technology on organizational adaptability. On a case example, (Choi et al., 2018) suggest that predictive analytics enhances sensing capabilities because it helps firms to identify early supply disruption and demand variations. On the same note, as indicated by (Dubey, Gunasekaran, Bryde, et al., 2020), big data analytics also enhances the speed and coordination of decision-making processes, thus, increasing supply chain responsiveness. The industry 4.0 technologies that allow firms to revolutionize the operations and enhance real-time visibility in the supply chains are the Internet of Things (IoT), cyber-physical systems, and cloud platforms (Frank et al., 2019; Tortorella et al., 2021).

Regardless of these developments, numerous empirical studies adopt a massively aggregated approach to DCV, which is that digital transformation is perceived as a single ability. This aggregation compromises theoretical accuracy since not all the digital technologies have the same contribution to the processes of dynamic capability. As an example, predictive analytics is mainly used to drive sensing and decision intelligence, whereas Industry 4.0 integration can offer infrastructure that can drive operational transformation and reconfiguration. It is therefore critical to isolate these capabilities in order to know how digital transformation can produce adaptive performance results.

2.3 Evolution of Digital Capability Models in Supply Chain Research

Direct Digital Capability- Performance Models

The former stream looks into direct correlations between digital technologies and performance results. The existing body of Industry 4.0 research examines the effectiveness of digital integration in enhancing the operational efficiency, cost-performance, or the supply chain agility (Frank et al., 2019; Núñez-Merino et al., 2020). On the same note, digital innovation studies tend to focus on the use of technology as the source of productivity and competitiveness (Iftikhar et al., 2024).

These works can be useful in understanding the advantages of digitalization on its operations. But very often, they do not have a clear theoretical foundation in dynamic capability processes. Digital technologies are regarded as a set of undifferentiated technological resources instead of the ability to support sensing, seizing, or transforming activities. Consequently, these models do not give a significant explanation of how digitalization enhances the adaptability capacity of firms in turbulent environments.

Digital Capability - Resilience - Performance Models

The second research stream presents the concept of supply chain resilience as an intervening variable. Multiple studies indicate that the resilience of digital analytics is enhanced through better visibility of the supply chain, detection risks, and coordination. To illustrate, (Wamba et al., 2017) prove that the capability of big data analytics enhances the performance and agility of the supply chain. Equally, (Bahrami et al., 2022) demonstrate that analytics capability enhances resiliency in supply chains, which, in turn, enhances operational performance.

These works are a significant theoretical advancement of considering resilience as an adaptive intermediate ability. They however usually concentrate on one digital capability, which in most occasions is analytics or big data. As a result, they do not consider the supportive nature of digital infrastructure technologies like Industry 4.0 integration, which can offer the connectivity and the operational flexibility required to execute analytics insights.

DCV-Based Digital Transformation Models

A less but increasingly sizeable body of work directly uses Dynamic Capabilities View to describe digital supply chain transformation (Bag & Pretorius, 2022; Dubey et al., 2019). These studies are recognizing the fact that digital technologies provide firms with the capacity of sensing disruption, coordinating resources, and restructuring operations.

Despite the fact that these studies contribute to the theoretical knowledge, there are still a number of limitations. To begin with, digital capabilities have been thought of as aggregated variables, concealing the individual contributions of various technologies. Second, the concept of supply chain resilience is seldom viewed as a higher-order dynamic capability, which converts sensing and transforming activities into sustainable performance consequences. Third, most of the empirical research concentrates on developed economies and emerging market situations are not well explored. Table 1 summarizes key theoretical approaches identified in the literature.

Table 1: Evolution of Digital Capability Models in Supply Chain Research

Study	**Theory**	**Digital Capability Type**	**Role of SCR**	**Model Structure**	**Context**	**Key Limitation**
(Teece et al.,1997)	DCV	General capabilities	Not examined	Conceptual	—	No digital disaggregation
(Teece, 2007)	DCV micro foundations	Sensing–transforming	Not operationalized	Conceptual	—	No empirical supply chain testing
(Wamba et al., 2017)	Resource-based view	Big data analytics	Mediator	SEM	Global	Single digital capability
(Dubey, et al., 2020)	DCV	Big data analytics	Antecedent to resilience	SEM	Developing	No Industry 4.0 integration
(Frank et al., 2019)	Industry 4.0 maturity	I4.0 adoption	Not central	Direct effect	Europe	No mediation logic
(Bahrami et al., 2022)	DCV	Analytics capability	Mediator	SEM	Developing	No digital infrastructure capability
(Núñez-Merino et al., 2020)	SLR	Industry 4.0	Not central	Review	Global	No empirical testing

Source: Authors own work

This synthesis highlights significant theoretical fragmentation in the existing literature.

2.4 Identified Research Gaps

The systematic review uncovers three significant gaps in literature.

Gap 1: Deficit in Capability Disaggregation: The majority of the studies take the digital transformation as one aggregated construct. There is scanty research that specifically identifies the ability to perform predictive analytics and its absence of digital infrastructure. These capabilities have various roles within the DCV framework, as predictive analytics improves sensing capabilities, whereas Industry 4.0 integration allows reconfiguring the operation and resources. Such disaggregation is not provided, which restricts theoretical clarity as to the contribution of digital technologies to adaptive supply chain performance.

Gap 2: Higher-Order Capability Conceptualization: In spite of the fact that a number of studies acknowledge the significance of supply chain resilience, it is commonly considered as an operational result or a medium variable. Nonetheless, resilience in the context of DCV could be seen as an overarching dynamic capability that allows firms to absorb, adjust their operation and sustain performance in the face of disruption (Ivanov et al., 2019). Empirical research does not often develop resilience as a conceptual framework of how sensing and transforming abilities lead to a sustainable performance output.

Gap 3: Digital Capability Models in the Emerging Economies: The current body of empirical studies is disjointed, and mostly biased towards developed economies. Supplies chain volatility and infrastructure constraints as well as institutional complexity are usually more common in emerging markets. Such circumstances render digital capabilities significant especially to the adaptability of organizations. Nevertheless, predictive analytics, Industry 4.0 integration, resilience, and sustainability have seldom been tested empirically in such connections in an integrated way.

2.5 Theoretical Positioning and Research Model.

Instead of developing a new theoretical paradigm, this work builds up on the Dynamic Capabilities View through the incorporation of several digital capabilities in one analytic model. Particularly, the study makes contributions to the literature in three aspects. It breaks digital transformation down into two analytically distinct capabilities, first: Predictive analytics that is AI related and improves sensing and decision intelligence as well as integration of Industry 4.0 that can transform operations and reconfigure resources. Second, it conceptualizes the supply chain resilience as a second order dynamic capability that transforms the sensing and transforming processes into sustainable outcomes of the supply chain performance. Third, it is a study that empirically tests this integrated model in the food manufacturing industry of an emerging economy where there is high rate of disruption and sustainability pressures in supply chains.

This study operationalizes the micro foundations of dynamic capabilities as proposed by (Teece, 2007) in digitally enabled supply chains and, therefore, overcomes the aggregation constraints of earlier studies and has a more detailed description of the way digital technologies can lead to resilience and sustainability. On the basis of these theoretical insights, the next section constitutes the research hypotheses and conceptual framework, according to which the empirical analysis will be developed.

3. Theoretical Foundation and Hypothesis Development

Given the growing levels of uncertainty and complexity in the world, the supply chains will be changing: the previously efficiency-driven systems are changing into resilient and sustainable models. The study is rooted in Dynamic Capabilities View (DCV), which holds that developed capability that enables organizations to sense, seize and reconfigure to respond to the volatility in the environment can give

sustained competitive advantage to such organizations (Teece et al., 1997; Teece, 2007) . In this regard, the concept of Industry 4.0 (I4.0) integration and AI Predictive Analytics (ADPA) is considered a digital dynamic capability. I4.0 technologies, such as the IoT, cyber-physical systems, and cloud computing help to increase transparency and allow firms to control operations in real-time, automate the decision-making process, and dynamically change processes, which are related to the sensing and reconfiguring elements of DCV (Bag & Pretorius, 2022). In the same vein, ADPA will help businesses predict disruptions by examining big data to enhance resilience and forecasting, which enhances proactive preparation and decision-making (Choi et al., 2018; Dubey et al., 2019). Such digital capabilities have a direct implication in the Supply Chain Resilience (SCR), or in other words, the capacity of a supply chain to withstand, recover or adapt to the impacts of disruptions. The SCR has been conceptualized as a dynamic capability process that fulfils the interconnection between technology adoption and the sustainability performance(Christopher & Peck, 2004). Finally, Sustainable Supply Chain Performance (SSCP) reflects the integration of economic, environmental, and social objectives into supply chain operations. Enhanced SSCP is achieved through the combined effect of I4.0 and AI analytics, both directly and indirectly via SCR, which allows firms to implement sustainable practices even during disruption events (Bag et al., 2020; Zhu et al., 2012). Lastly, we present our hypotheses to substantiate our constructs and their relationships, as shown in Figure 1.

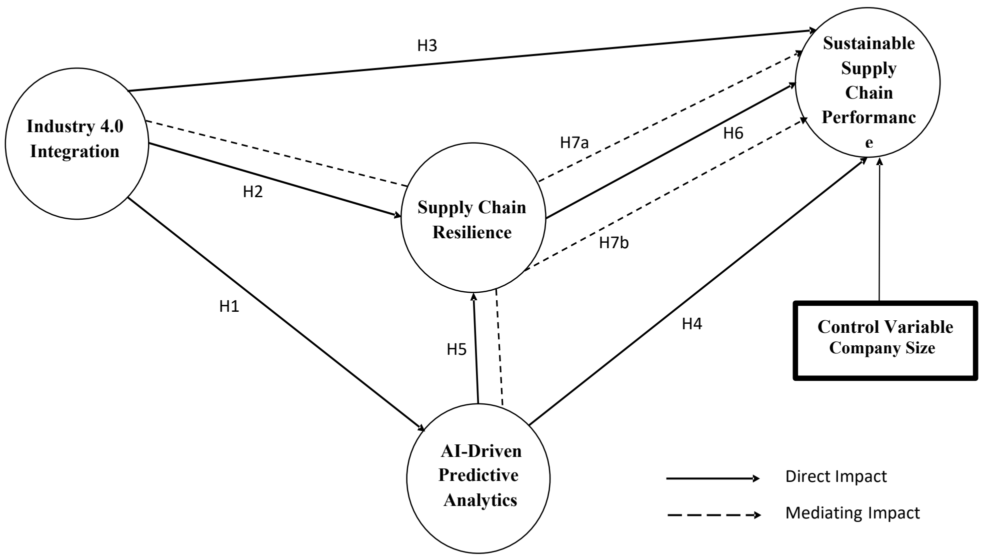

Figure 1: Theoretical research Model (Source: Authors own work)

We draw a relationship with I4.0I and SSCP to explore into the direct effects of I4.0I on SSCP and place out seven research hypotheses premised on DCV. Based on the theoretical background provided above, Figure 1 presents the research model, according to which AIDAP affects SCR and SSCP and SCR as a mediating factor.

3.1 Impact of I4.0I on AIDPA

Industry 4.0 (I4.0) The fourth revolution in the field of industry is the digitalization of production and supply chains, achieved using innovative technologies including but not limited to the Internet of Things (IoT), cyber-physical systems, big data, and cloud computing. These applications produce huge datasets in real-time, the very bedrock of moving forward with AI-based predictive analytics (AIDPA). This interoperability via I4.0 framework makes the data acquisition, connectivity, and supply chain interoperability in building different predictive models in understanding patterns, predictions, and suggestions of adaptive measures. Predictive analytics using AI is the use of high-quality, grained and real-time packed data streams, which I4.0 systems can greatly improve. For example, sensors built into the production lines or logistics property provide a constant flow of data which can be applied by the AI models to identify anomalies, demand fluctuations, or inventory flows optimization. According to (Wamba et al., 2017), the combination of I4.0 and big data analytics helps to increase predictive functionality due to the ability to provide visibility and transparency within the supply networks. On the same note, (Frank et al., 2019a) highlighted that the maturity of I4.0 systems is usually matched with the maturity on analytics at the company level, especially towards using AI to get predictive information. Additionally, (Choi et al., 2018) claim that Industry 4.0 is a technological enabler of AI-based analytics since it is the combination of operational technologies (OT) and information technologies (IT), and it is necessary in dynamic decision-making. (Dubey et al., 2024) also emphasized that since the I4.0 architecture and predictive analytics ability are aligned, the firms are significantly strengthened in terms of their agility and responsiveness to breaks.

H1: I4.0I has a significant positive impact on AIDPA.

3.2 Impact of I4.0I on SCR

Industry 4.0 Integration (I4.0) is the next big technological step involving such new technologies as the use of cyber-physical systems (CPS), Internet of Things (IoT), cloud computing, advanced robotics, and real-time analytics. All these technologies contribute to elevated Supply Chain Resilience (SCR) because they allow firms to respond, adapt, and sense better to the shocks in their supply chain. I4.0 offers greater transparency, connectedness and artificial intelligence support to decision making. As an example, IoT-powered sensors and smart devices enhance the real-time tracking of supply, equipment and transportation that can be used to determine bottlenecks or disturbances prior to their progression of the issue to larger proportions. Cloud infrastructure allows improved information sharing and supply chain visibility, and autonomous systems and robotics provide flexibility and the ability to respond quickly to situations. (Bag et al., 2021) emphasize that the I4.0 technologies enhance the flexibility and responsiveness of operations, which is vital to resilience. According to (Dubey et al., 2019) digital transformation enables companies to respond quickly to a global disruption and recover effectively due to the pandemic or geopolitical tensions. (P. Chowdhury et al., 2021) also went on to point out that the adoption of I4.0 promotes learning and dynamic functionality of an organization that helps to recover faster and reduce the risks. Another study by (Xu et al., 2021) reached the same conclusion that digital supply chain twins and IoT enhance sensing capabilities of firms making them more resilient in unpredictable environments. Further, the concept of the digital supply chain twin was presented by (Ivanov et al., 2019b) who suggested that simulation and optimization tools under the influence of I4.0 enabled firms to test various scenarios of recovery and resilience optimization of their strategies in advance. Therefore, I4.0 integration not only simplifies the operations but resilience is the key principle integrated into the very nature of supply chains-assisting the firms to survive, adapt and thrive in the arms of continuous change.

H2: The adoption of I4.0I technologies positively influences the development of SCR.

3.3 Impact of I4.0I on SSCP

The integration of Industry 4.0 technologies, including cyber-physical systems, IoT, big data analytics, and artificial intelligence, has transformed supply chain operations by enabling real-time data collection, predictive analytics, and automation. These advancements allow organizations to optimize resource utilization, reduce waste, and improve operational efficiency, thereby directly enhancing sustainable supply chain performance (Birkel & Müller, 2021) . Industry 4.0 will enable data-driven decision-making, enabling managers to realize inefficiencies and adopt strategies which are congruent with sustainability objectives, including energy-saving and minimizing environmental impact (Kumar et al., 2022). Moreover, Industry 4.0 helps to sustain practices by improving transparency and traceability of materials through technologies like IoT and blockchain, enabling effective reuse, recycling, and environmentally responsible resource management (Marak et al., 2024). Consisting of these capabilities, Industry 4.0 not only improves operational performance but also benefits operations with environmental, economic, and social sustainability aspirations.

H3: I4.0I has a robust positive impact on SSCP.

3.4 Impact of AIDPA on SSCP

In supply chains, AI predictive analytics (AIDPA) predicts future trends, disruption, and optimization of process decisions through machine learning, statistical modelling, and analysis of big data. Predictive analytics could be applied to operations to help companies predict demand and reduce excess inventory, and use their resources to their fullest potential, thus directly resulting in sustainable supply chain performance(Dubey et al., 2020). To enable informed and proactive decisions in the future and achieve energy saving, minimize wastefulness or maximize the efficiency in the processes, big data can be processed by the AIDPA (Choi et al., 2018b). Moreover, AI-based predictive analytics can help organizations to be more sustainable, and with more efficient logistics, more energy-efficient production cycles, and improved management of suppliers, the boundaries of the goals of environmental, economic, and social sustainability are also broadened (Frank et al., 2019). Therefore, AI predictive analytics is a crucial means with the help of which organizations may achieve measurable sustainability in performance. The AI analytics would enable organizations to formulate informed sustainability objectives and track the results in real-time, by forecasting future trends and results. The companies implementing those analytics will be defined by better indicators of operating efficiency and sustainability, such as a reduced carbon footprint and reduced waste.

H4: The effect of AIDPA on SSCP is positive.

3.5 Impact of AIDPA on SCR

Nowadays, Artificial Intelligence (AI) or, more precisely, what is better called predictive analytics, is considered to be among the strongest resilient supply chain levers. In addition to predicting disruptions and anticipating undesirable outcomes, AI can help supply chains identify anomalies and, moreover, can forecast such disruptions and predict adverse outcomes based on real-time data, machine intelligence, and clever algorithms (Choi et al., 2018; Dubey et al., 2019). The capabilities minimize uncertainty and allow a supply chain to rapidly react to any exogenous

shocks (demand fluctuations, supplier failure, or geopolitical shocks). Predictive analytics aims to provide resilience through improvements to early warnings, optimal decision-making based on the uncertain environment, and simulation of disruption conditions. It is then mentioned that AI-based systems will be able to provide 24/7 monitoring of the parameters in the operations and the risk exposure and propose mitigation operations based on the time(Raj et al., 2020). That is central to the rise of nimble and agile supply chains. According to (Wamba et al., 2017), the first and most significant aspects of the supply chain resilience are enhanced by AI: flexibility and responsiveness of an organization. Moreover, (Bag et al., 2021) explain that used in an operational excellence strategy, AI makes an organization immune to the burden of re-engineering its operations, which is a hallmark of the Dynamic Capabilities Framework (Teece et al., 1997). It is here that AI assists in those functions that assist an organization to sense signals in the environment, feel the opportunity, and reorganize operations in a manner that sustains continuity and stability. In addition, (Ivanov et al., 2019) note that AI and digitalized risk analytics have a positive interdependence that can be used to reduce the impact of any supply chain contingency. There will be no need to intervene to re-route the items to be shipped, to reassign resources, and production focus, which are the essentials of resilience in AI-based supply chains. Hence, as strategically applied, AI could go beyond an efficiency tool; it will become a strategic asset to add flexibility, resilience, and capacity to the supply chains.

H5: AIDPA have a positive influence on the SCR.

3.6 Impact of SCR on SSCP

Supply chain resilience (SCR) can be defined as the capacity of a supply chain to forecast, prepare, respond and recover against disruption, thereby sustaining continuity and safeguarding long-term performance. During challenging periods, resilience in the framework of sustainable supply chain performance (SSCP) is key to meeting environmental, financial and social sustainability objectives. Empirical research has demonstrated that resilience of the supply chain would help in better managing the disruption associated with a natural disaster, economic changes, and unavailability of supplies to minimize negative sustainability impacts. In order to be able to explain this fact in a study, it has been proven that strong supply chains could bring uniformity to products and offer supplying quality and, above all, through resources, which will contribute to a more stable environment (Scholten et al., 2019). Besides that, the transition to the needs of the new market and regulations that positively influence the ability to sustain an economy in both aspects of minimizing costs and compliance will become possible with a good supply chain (M. M. H. Chowdhury et al., 2019).

Moreover, resilient supply chains that have been disrupted are more socially responsible in the areas of fair labor, community and ethical sourcing (Birkie et al., 2017). It is an integrative approach to sustainability that focuses on the importance of resilience in achieving overall sustainable performance.

H6: SSCP is positively influenced by SCR.

3.7 The Mediating Role of Supply Chain Resilience (SCR)

Supply chain resilience (SCR) has now become a hot dynamic capability allowing organizations to predict, absorb, and respond to disruption without compromising long-term sustainability targets. Resilience is an important intermediary factor in the context of Industry 4.0 integration and predictive analytics supported by (AIDPA), since it can convert technological capabilities into sustainable performance outputs.

In the case of Industry 4.0 implementation (H7a), the smart technologies represented by IoT, big data, and cyber-physical systems offer the foundation to achieve efficiency and transparency, but their full sustainability potential can be achieved only when organizations build resilient supply chains. Resilience ensures that the technological benefits translate into operational stability, waste reduction, and optimized resource use, thereby enhancing sustainable supply chain performance (Birkel & Müller, 2021; Ivanov, Dolgui, et al., 2016). Without resilience, even advanced Industry 4.0 adoption may not safeguard supply chains from unexpected disruptions, limiting their contribution to sustainability.

In the case of Industry 4.0 implementation (H7b), the resilience directly depends on the capabilities of risk forecasting, demand variation forecasting, and process optimization, which in turn have an effect on preparedness and adaptive capacity. Predictive insights can enable supply chains to make proactive moves to ensure that they are less vulnerable to disruptions and able to recover faster. (Choi et al., 2018; Dubey et al., 2020). With the increased resilience, efficiency is not the only positive aspect of predictive analytics, resulting in quantifiable differences in the environmental, economic, and social aspects of sustainability. In this regard, SCR will become more like a facilitator; the competences acquired in the course of integrating Industry 4.0 and AI-predicted analytics will be converted into long-term sustainable supply-chain performance.

H7a: Supply chain resilience mediates the relationship between Industry 4.0 integration and sustainable supply chain performance.

H7b: Supply chain resilience mediates the relationship between AI-driven predictive analytics and sustainable supply chain performance.

4. Research Methodology

The research approach will use a quantitative approach with an empirical research design that can help explore the boundaries of the hypothesis based on the relationships that exist between AIDPA, I4.0I, SCR, and SSCP. Considering the exploratory and confirmatory purposes of the research, an empirical data collection design with survey was used, which provides an opportunity to measure the latent constructs and connect them based on a statistical model (Hair et al., 2014; Podsakoff et al., 2003). In order to examine the theoretical model as well as to analyses the relation between the variables posited, the study relied on Partial Least Squares Structural Equation Modelling (PLS-SEM) by means of the Smarts 4.0 program. This approach can be used in predictive modelling or complex path analyses, and in studies with relatively small to middle-size samples ("Partial Least Squares Structural Equation Modeling," 2022). Besides, PLS-SEM works on theory development effectively in cases where the model has more than two latent constructs, mediation (like supply chain resilience), and reflective indicators (Wamba et al., 2017).

4.1 Survey instrument development

A structured questionnaire was prepared on the basis of survey was prepared to empirically test a proposed dynamic capabilities framework that comprises AI-driven predictive analytics and the I4.0 technologies, SCR, and SSCP. The existing literature was followed to design measurement items per construct and implement a contextualization of the measurements into the operational setting of the Bangladeshi food manufacturing industry and its digital transformation progress (Bag & Pretorius, 2022; Dubey et al., 2019; Ivanov, Pavlov, et al., 2016). Each of the constructs including exogenous (e.g., AI adoption, Industry 4.0 integration) and endogenous (e.g., supply chain resilience, sustainable performance) was operationalized as reflective ones (Choi et al., 2018; Frank et al., 2019).To achieve content validity and context relevance, followed by the analysis of the results of the questionnaire pre-test, using five industry practitioner experts in the supply chain analytics and three academic professional experts in sustainability performance measurement was critical (DeVellis, 2016; Jabbour et al., 2019). These professionals evaluated the readability, pertinence and comprehensiveness of the items, which gave the essential comments which resulted in the subsequent adjustment of question wordings and construct congruence. The last instrument used a five points Likert scale that considers the range of perception and attitude of the respondents that, with a range of 1 = strongly disagree to 5 = strongly agree, adequately measures the perception and attitude expressed by respondents (Dwivedi et al., 2023; Fosso Wamba et al., 2015). All independent and dependent constructs were represented as reflective variables, as illustrated in Table 2.

Table 2: Measurement Items

Construct	Type	Measures	Sources
AI-Driven Predictive Analytics (AIDPA)	Reflective	AIDPA1: Our firm uses predictive models to forecast supply and demand fluctuations AIDPA2: Our firm applies AI tools to detect disruptions proactively. AIDPA3: AI is integrated into our operational decision-making processes. AIDPA4: We leverage machine learning to optimize inventory and production planning.	(Choi et al., 2018d; Wamba et al., 2017c)
Industry 4.0 Integration (I4.0)	Reflective	I40I1: Our firm adopts interconnected digital technologies like IoT and cloud systems. I4.0I2: We use automated data sharing across supply chain partners. I4.0I3: Smart technologies support real-time decisions in our operations. I4.0I4: Our production systems are equipped with sensors and cyber-physical systems. I4.0I5: We use digital dashboards for real-time monitoring and control.	(Bag & Pretorius, 2022a; Frank et al., 2019c)
Supply Chain Resilience (SCR)	Reflective	SCR1: Our supply chain can quickly respond to sudden disruptions. SCR2: We have contingency plans and adaptive capabilities. SCR3: We recover efficiently from disruptions.	(Dubey et al., 2019; Ivanov et al., 2019)
Sustainable Supply Chain Performance (SSCP)	Reflective	SSCP1: Our firm achieves strong environmental performance. SSCP2: Our firm achieves good social performance. SSCP3: Our firm achieves strong economic performance. SSCP4: Our supply-chain practices increase resource efficiency. SSCP5: We comply with relevant	(Das, 2017; Zhu et al., 2012)

		environmental and social standards and report on sustainability.	

Source: Authors own work

4.1.1 Questionnaire Design

The elements of the research questionnaire, such as Construct, components, number of items (observed variables), kind of variable, and sources used in their construction are listed in table 1.

4.1.2 Reliability and validity of the questionnaire

Pilot test is conducted to determine the reliability and validity of the questionnaire was undertaken before the actual data collection. The pilot survey entailed 30 participants in the food manufacturing industry including the professionals in the field of supply chain, logistics, and operations management. Table 3 presents the internal consistency and measurement validity of the survey instrument.

The internal consistency of the questionnaire was determined by alpha coefficients of Cronbach which measures the consistency of items within a construct. The alpha values that exceed 0.70 are usually deemed satisfactory and represent the satisfactory measurement scale reliability (Hair et al., 2022). The findings illustrate that all the constructs surpassed this recommended threshold, which points at high internal consistency. In particular, the Cronbach alpha of the AI-Driven Predictive Analytics (AIDPA), Industry 4.0 Integration (I4.0I), Supply Chain Resilience (SCR), and Sustainable Supply Chain Performance (SSCP) were 0.838, 0.810, 0.861, and 0.813, respectively. These findings indicate that the constructs of the questionnaire items are always consistent.

Besides the alpha of Cronbach, composite reliability (CR) was also used to verify internal consistency reliability. A composite reliability value of greater than 0.70 shows that the structural equation modeling study has sufficient reliability (Hair et al., 2022). This was met by all constructs in this study with a composite reliability score ranging between 0.866 and 0.915, which showed that the measurement model was very reliable.

In order to measure convergent validity, the average variance extracted (AVE) was computed in relation to each construct. Values of AVE that exceed 0.50 signify that a construct accounts over fifty percent of the variance of its indicators, which is an affirmation of satisfactory convergent validity (Fornell & Larcker, 1981). All construct values were found to be between 0.564 and 0.783, which is higher than the prescribed value and proves a sufficient convergent validity of scales.

In addition, the validity of the questionnaire concerning its content was also carried out by experts before the pilot survey. The questionnaire was checked by a panel of eight experts comprising of five industry professionals, and three academic researchers in the field of supply chain management to determine the clarification, relevance, and suitability of the measurement items. According to their response, slight adjustments on the wordings were implemented to enhance clarity and compatibility to the theoretical constructs. This professional validation measure helped to make sure that the questionnaire was effective in terms of conceptualizing the ideas of AI-driven predictive analytics, Industry 4.0 integration, supply chain resilience, and sustainable supply chain performance.

Table 3: The reliability of the questionnaire using Cronbach's alpha, Composite Reliability and AVE.

Construct	Cronbach's Alpha	Composite Reliability	AVE
Industry 4.0 Integration (I4.0I)	0.810	0.866	0.564
AI-Driven Predictive Analytics (AIDPA)	0.838	0.891	0.672
Supply Chain Resilience (SCR)	0.861	0.915	0.783
Sustainable Supply Chain Performance (SSCP)	0.813	0.870	0.573

Source: Authors own work

4.2 Data Collection and Sampling Design

This research study was conducted using empirical evidence gathered among the individuals who work in the food manufacturing sector in Bangladesh, the country where this particular industry is an important part of the national economy and presents the highly dynamic chain of supply. The sector has been strategically selected since this industry is especially vulnerable to supply chain shocks, fluctuating demand, and inefficiencies in the resources utilized and hence provides a perfect environment to examine how AI-driven predictive analytics and Industry 4.0 technologies that increase supply chain resilience and sustainable supply chain performance can be adopted (Ivanov et al., 2019; Pal et al., 2024).An administered questionnaire survey was drawn with valid constructs used in previous research, which consisted of the major constructs of the research. The first questionnaire was checked by the subjects and professionals working in the field of study and consisted of content validity (Hair et al., 2014; Saunders et al., 2021).Then, it was distributed via a mixed-mode method, i.e., given online (through Google Forms, via email).

The completed questionnaire comprises 194 valid responses among 490 of mid and senior level professionals employed in logistics, procurement, operations and supply chain management functions within medium and large food manufacturing companies in the country of Bangladesh. The research sample included respondents who had direct access to the operational process and the development of technological initiatives related to the use of the concept of predictive analytics, tracking through IoT, automatic quality control, and sustainable (economic, environmental, social) performance (Bag & Pretorius, 2022; Wamba et al., 2017). This makes sure that the subjects had the expertise required in the domain to assess the relations between AI adoption, Industry 4.0, resiliency, and sustainability adequately.

The sampled frame included those who were professionals within organizations of large-scale capacity (500-5,000 employees) and small-scale capacity (0-500 employees) manufacturing establishments. Among the 194 responses received (about 40% response rate), a good percentage of respondents had a practical experience in the field of Industry 4.0 technologies (about 65 percent) and a smaller percentage had knowledge and/or implemented AI-powered forecasting or predictive analytics tools in their business (about 58 percent). Such an inclusion criterion played a significant role because these are associated with the dynamic capabilities viewpoint, as well as making sure that digital transformation, resilience, and circularity constructs are valid (Dubey et al., 2018; Teece et al., 1997c). All respondents differed in terms of the experience with 46.91% having 6-11 years, 28.87% having 12-16, and 24.23% having more than 17 years of experience in the industry. Their working areas also represent a high degree of heterogeneity in the area of logistics, management of materials, planning, and together with AI, which makes the findings even more generalizable to the field of manufacturing supply chains (Choi et al., 2018; Wamba et al., 2017). Such an informed choice of respondents meant that this population sample would be considerably knowledgeable in assessing the intricate dependency between the AI adoption, the integration of I4.0, the resilience of the supply chain, and sustainable supply chain performance. This analysis reveals notable differences in the demographic and professional profiles of the respondents. A summary of the sample characteristics is provided in Table 4.

Table 4 : Summary of the Sample Characteristics (Total Sample, n = 194)

Criteria	Type	Number	Response Proportion (%)
Gender	Male	125	64.43%
	Female	69	35.57%
Company Capacity	Small (0–500 employees)	24	12.37%
	Large (500–5,000 employees)	170	87.63%
Experience	6–11 years	91	46.91%
	12–16 years	56	28.87%
	17–24 years	47	24.23%
Designation	Operations Executive	38	19.59%
	Planning Coordinator	12	6.19%
	Procurement Head	17	8.76%
	Materials Coordinator	9	4.64%
	Supply Chain Head	58	29.90%
	Logistics Manager	18	9.28%
	Other Managerial Roles	7	3.61%

Source: Authors own work

4.3 Non-response Bias

Since this research was based on survey information, the non-response bias was also considered so as to make sure that the sample sample obtained is representative enough to represent the target population. Non-response bias happens when the respondents who attend the survey do not do so normally compared to those who do not attend the survey. The process suggested by (Armstrong & Overton, 1977) was used as a method of evaluating this problem.

In this manner, the obtained responses were categorized into early respondents and late respondents according to time the questionnaires were submitted. The independent samples t-test was to be used in comparing the mean values of the main constructs between the early and late respondent groups. Table 5 displays the findings of the analysis. The results show that all the constructs, such as AI-Driven Predictive Analytics ($p = 0.122$), Industry 4.0 Integration ($p = 0.633$), Supply Chain Resilience ($p = 0.318$), and Sustainable Supply Chain Performance ($p = 0.229$), have no statistical significance ($p > 0.05$) between early and late respondents.

Because the comparisons of all the differences did not indicate any statistically significant differences, the findings indicate that non-response bias is not a grave issue in this study. Thus, the data can be said to be representative of the target population and it can be further analyzed using statistics.

Table 5: Non-Response Bias Test (Early vs Late Respondents)

Construct	Early Mean	Late Mean	p-value
AI-Driven Predictive Analytics	3.52	4.07	0.122
Industry 4.0 Integration	3.88	3.86	0.633
Supply Chain Resilience	3.14	3.51	0.318
Sustainable Supply Chain Performance	3.30	3.75	0.229

Source: Authors own work

5. Data Analysis and Results

To analyses the theoretical framework, we proposed that we use the SmartPLS 4.0 built on Partial Least Squares-Structural Equation Modelling (PLS-SEM) method. PLS-SEM is specifically favorable to the study we are conducting since it is prediction-oriented, is not affected by small-to-medium sample size, and can support the consideration of complex models inclusively of direct and indirect relationships ("Partial Least Squares Structural Equation Modeling," 2022; Peng & Lai, 2012). In addition, PLS-SEM does not demand severe specializations in the data normalcy, thus ideal in practical application with empirical data in a complex environment, such as the design of supply chain resilience and circular sustainability (Dubey et al., 2019; Lim et al., 2017). PLS-SEM is also an effective way to estimate both the measurement and structural models simultaneously, which allows us to stringently test hypothesized relationships, such as Supply Chain Resilience mediating them (Bag & Pretorius, 2022; Ivanov et al., 2019). In addition to this, it views measurement errors as opposed to the Covariance-Based SEM (CB-SEM), and as such, renders better and more realistic estimates (Henseler et al., 2015; Kock, 2019). Of the responses we have, 194 were ethical, hence far more than the recommended size. Such a large sample size promises enough statistical power, model stability and reliability of results. Using SmartPLS 4.0, we both checked the measurement model in terms of reliability and validity and the structural model in terms of path relationships and hypotheses. The strength of our research findings is supported by the exhaustive nature of our analysis, which further increases the validity and generalizability of our research findings.

5.1 Measurement Model

Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4.0 was used to measure the model. PLS-SEM was selected as appropriate because it is appropriate to use complex models and also, the PLS-SEM dissolves the distinction between instrumental variables and outcome variables compactness to deal with small sample size, which does not necessitate the use of data which are normally distributed and hence can be used even with a small set of data. This evaluation was done by measuring internal consistency reliability, convergent validity and indicator reliability of all latent constructs.

Internal consistency was measured through Cronbach's alpha(α), rho_A, and composite reliability (CR). ("Partial Least Squares Structural Equation Modeling," 2022) suggest that reliability of Cronbach alpha and CR should be over 0.70 to be accepted. This was observed with all the constructs passing this mark, as shown in Table 6. To illustrate, the construct Industry 4.0 Integration got 0.810 and 0.866 on the Cronbach alpha and CR respectively; AI-Driven Predictive Analytics had 0.838 and 0.891

on their part respectively. Likewise, high internal consistency can also be obtained in SCR and SSCP with 0.915 and 0.870 as CR, respectively.

Convergent validity was assessed using the Average Variance Extracted (AVE) and factor loadings. The acceptable AVE values are more than 0.50 (Fornell & Larcker, 1981b).The above-threshold is exceeded by all the constructs, and the AVE values lie between 0.564 (Industry 4.0 Integration) and 0.783 (Supply Chain Resilience), which helps to define the convergent validity. Moreover, standardized factor loadings were greater than the cutoff value of 0.70 and barely below (such as I4I2:0.706 and SSCP2: 0.704) in all separately measured items. However, because they did not affect overall reliability, and they were near the cutoff, they were retained ("Partial Least Squares Structural Equation Modeling," 2022b).

Table 6: Reliability and Convergent Validity

Construct	Measurement Items	Factor Loadings	Cronbach's alpha	Composite Reliability (rho_a)	Composite reliability (rho_c)	AVE
I4.0I	I4.0I1	0.729	0.810	0.822	0.866	0.564
	I4.0I2	0.706				
	I4.0I3	0.761				
	I4.0I4	0.800				
	I4.0I5	0.755				
AIDPA	ADPA1	0.830	0.838	0.841	0.891	0.672
	ADPA2	0.795				
	ADPA3	0.836				
	ADPA4	0.818				
SCR	SCR1	0.868	0.861	0.861	0.915	0.783
	SCR2	0.899				
	SCR3	0.887				
SSCP	SSCP1	0.741	0.813	0.823	0.870	0.573
	SSCP2	0.704				
	SSCP3	0.793				
	SSCP4	0.832				
	SSCP5	0.707				

Source: Authors own work

The discriminant validity allows each construct of the model to be unique and to measure conceptually dissimilar phenomena. There are two techniques of measuring discriminant validity via Fornell Larcker Criterion and via Heterotrait- Monotrait Ratio of Correlation (HTMT) that are utilized in PLS-SEM with SmartPLS 4.

The Fornell Larcker Criterion is a test used to determine discriminant validity, and it compares the square root of the sun Average Variance Extracted (AVE) of one construct with inter-construct correlations. To achieve acceptable discriminant validity, the square root of the AVE (diagonal value) of a construct should surpass the correlation between that construct and all other constructs shown in Table 7 (Fornell & Larcker, 1981; "Partial Least Squares Structural Equation Modeling," 2022b).

Table 7: Discriminant Validity - Fornell-Larcker Criteria

Constructs	AIDPA	SSCP	I4.0I	SCR
AIDPA	0.82			
SSCP	0.54	0.757		
I4.0I	0.537	0.455	0.751	
SCR	0.672	0.6	0.464	0.885

Source: Authors own work

From the Table 7 we got all diagonal items are larger than the corresponding inter construct correlations, and this confirms the discriminant validity according to the Fornell and Larcker criterion.

A more demanding discriminant validity measurement is the Heterotrait-Monotrait (HTMT) ratio. It makes an evaluation of the quotient between-construct correlations (heterotrait-hetero method) and within-construct correlations (monotrait-hetero method). In this respect (Henseler et al., 2015), state that discriminant validity can be established only in case the HTMT values fall below 0.85 (more conservative) or 0.90 (more liberal threshold) which are shown in table 7.

Table 8: Discriminant Validity (HTMT Ratio)

Constructs	AIDPA	SSCP	I4.0I	SCR
AIDPA				
SSCP	0.641			
I4.0I	0.626	0.539		
SCR	0.784	0.707	0.531	

Source: Authors own work

In Table 8 the HTMTs are all lower than the threshold of 0.85, thus ensuring a strong discriminant validity of the constructs.

5.2 Common Method Bias

In order to deal with the problem of Common Method Bias (CMB) that could be caused by the self-reported and single-source nature of data collection described, both process and statistical solutions were used. Procedurally, a number of steps were followed in reducing possible bias in designing the survey. The respondents were also assured of their anonymity as well as confidentiality, as they were told that there is no wrong or right answer to foster truthful and objective responses (Podsakoff et al., 2003). Questions of the survey were well-designed and properly worded not to be repetitive, and items belonging to different constructs were randomly distributed throughout the questionnaire to minimize priming effects and hang-up responses ("Common Method Variance in International Business Research," 2020; MacKenzie & Podsakoff, 2012). These methodologies assisted in reducing fatigue among the respondents and prevalent rater effects. Table 9 summarizes that statistically, the single-factor test by Harman was done by inserting all items into an unrotated exploratory factor analysis with SPSS.

In this analysis, the first factor had estimated a considerable percentage of less than 50 per cent of the overall variance, therefore showing that the common method variance is not of a serious issue (Podsakoff & Organ, 1986). In addition, SmartPLS full collinearity analysis was carried out as recommended by Kock (2015). All VIFs were far below the conservative limit of 3.3 across all latent constructs that indicating that the presence of large-scale multicollinearity and common method bias difficulties did not exist. The combination of the procedures provides empirical evidence with a stronger validity and reliability in regard to the impacts of AI-based predictive analytics and the integration of Industry 4.0 on the resilience of supply chains and the circular sustainability with the environmentalist in the Bangladesh food manufacturing sector.

Table 9: Results of Harman's Single-Factor Test Showing Total Variance Explained

Total Variance Explained						
Factor	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**		
	Total	**% Of Variance**	**Cumulative %**	**Total**	**% Of Variance**	**Cumulative %**
1	6.987	41.098	41.098	6.392	37.602	37.602
2	1.794	10.552	51.651			
3	1.384	8.141	59.792			
4	.890	5.233	65.025			
5	.766	4.507	69.532			
6	.678	3.991	73.523			
7	.627	3.687	77.210			
8	.582	3.425	80.635			
9	.478	2.814	83.449			
10	.450	2.645	86.094			
11	.408	2.398	88.492			
12	.401	2.362	90.854			
13	.377	2.220	93.074			
14	.370	2.177	95.251			
15	.298	1.754	97.004			
16	.273	1.607	98.611			
17	.236	1.389	100.000			
Extraction Method: Principal Axis Factoring.						

Source: Authors own work

To check the degree of multicollinearity in the measurement model, all reflective items VIF were analyzed with SmartPLS4. Multicollinearity arises when indicators have very high correlation, and it can bias the estimation of the path coefficients and cause overestimation of standard errors in the structural equation model. ("Partial Least Squares Structural Equation Modeling," 2022b) state and approximate values of VIF below 3.3 are normally acceptable, but the same authors state that values higher than that could indicate suspicious lateral collinearity (Kock et al., 2012). In the current research, table 10 shows the full range of values of VIF was between 1.465 and 2.449, with the indicators of both of AI-Driven Predictive Analytics (ADPA) and Circular Sustainability (CS) showing a value range of 1.695-2.001 and 1.466-2.021, respectively, with Industry 4.0 Integration (I4.0I) indicator showing 1.465-1.775 and Supply Chain Resilience (SCR Though SCR2 and SCR3 have a comparatively high VIF of (2.449 and 2.301 respectively), these values are not beyond acceptable standards and do not raise any multi-collinearity issues. These outcomes confirm that none of the indicators is dually pertinent to the others in its construct, and, therefore, the soundness of structural estimates will not be jeopardized. This is particularly relevant in research when we are studying interrelated constructs such as predictive analytics, Industry 4.0 technologies, resilience, and sustainability in the supply chains, we need to understand that in many cases, there inevitably may be conceptual overlaps. It is good in that it has no multicollinearity and the measurement model above does not undermine the next or future structural model diagnosis.

Table 10: Multicollinearity Test (Variance Inflation Factor)

Construct	Measuring Items	VIF
AIDPA	ADPA1	2.001
	ADPA2	1.724
	ADPA3	1.951
	ADPA4	1.695
SSCP	SSCP1	1.466
	SSCP2	1.535
	SSCP3	1.74
	SSCP4	2.021
	SSCP5	1.51
I4.0I	I4.01	1.775
	I4.02	1.694
	I4.03	1.522
	I4.04	1.753
	I4.05	1.465

SCR	SCR1	1.974
	SCR2	2.449
	SCR3	2.301

Source: Authors own work

5.2.1 Marker Variable Test for Common Method Bias

In order to further evaluate the possible existence of common method bias (CMB), a marker variable method was used, in accordance with the (Lindell & Whitney, 2001) and (Hulland et al., 2018) suggestions. The marker variable approach presents the variable that is theoretically irrelevant to the main variables of the study and tests its association with the key variables.

Company size was considered the marker variable in this research because it is not conceptually related to the main constructs that were reviewed in the model which included AI-driven predictive analytics, Industry 4.0 integration, supply chain resilience as well as sustainable supply chain performance. Each of the study constructs was analyzed on Pearson correlation with the marker variable.

Table 11 shows that the correlations between the marker variable and the overall constructs are very low, the value lies between -0.005 and -0.084 which is far short of the proposed value of 0.10. (Lindell & Whitney, 2001) state that low correlations lead to the conclusion that common method bias will not be problematic in the study due to the relationship between the constructs.

Table 11: Correlation with Marker Variable

Construct	Marker Variable	Correlation with Marker Variable
AI-Driven Predictive Analytics	Company Size	-0.084
Industry 4.0 Integration		-0.016
Supply Chain Resilience		-0.005
Sustainable Supply Chain Performance		-0.030

Source: Authors own work

Thus, it can be implied that the common method variance is not a critical threat to the validity of the results.

5.2.2 Endogeneity Assessment

In order to investigate the possible endogeneity challenges, the Gaussian copula method developed by (Park & Gupta, 2012) was used. Endogeneity can also occur when the explanatory variables are correlated with the error term thus producing biased estimates of the parameter. Based on the recommended process, the copula terms were created concerning the potentially endogenous constructs, which are AI-based predictive analytics (AIDPA) and Industry 4.0 integration (I4.0I). Regression models were then used to measure the statistical significance of these copula terms.

Conclusion of the results is in Table 12 states that the copula terms are statistically insignificant in both models. In particular, in the SCR model, the copula coefficients of AIDPA and I4.0I were not significant ($p = 0.188$ and $p = 0.968$, respectively). In the same way, the terms of copula were also not significant ($p = 0.473$ and $p = 0.059$) in the SSCP model. (Park & Gupta, 2012) describe insignificant copula as an indicator that there is no endogeneity in the model.

Table 12: Gaussian Copula Endogeneity Test Results

Dependent Variable	Copula Term	Coefficient (β)	p-value	Result
Supply Chain Resilience (SCR)	Cop_AIDPA	0.643	0.188	Not Significant
	Cop_I4.0I	-0.018	0.968	Not Significant
Sustainable Supply Chain Performance (SSCP)	Cop_AIDPA	0.345	0.473	Not Significant
	Cop_I4.0I	-0.832	0.059	Not Significant

Source: Authors own work

Thus, it can be concluded that endogeneity is not a severe menace to the validity of the structural relationships studied in the given work.

5.3 Hypothesis testing

We tested the structural model using path coefficients (β), t-test and p-value to determine the hypothesized association strength. The findings indicate that six of the alleged relationships are revealed to be statistically strong at the significance level of $p < 0.05$ meaning that the theoretical framework is empirically anchored to a large degree, as presented in Table 13. The most robust connection is known between the AI-Driven Predictive Analytics (ADPA) and the Supply Chain Resilience (SCR) ($\beta = 0.053$, $p < 0.001$), proving the important role of predictive capacity in increasing resiliency.

Moreover, the influence of the Industry 4.0 Integration is also high ($\beta = 0.056$, $p < 0.001$), as digital technologies serve as the drivers of predictive analytics in contemporary supply chains indeed (Frank et al., 2019). Moreover, Sustainable Supply Chain Performance (SSCP) is positively affected by both AIDPA and SCR, which leads to the assumption that resilience- and intelligence-based approaches result in the sustainability of the environment and operations, both in the short and in the long run (Bag & Pretorius, 2022; Jabbour et al., 2019). In part, SCR in AIDPA enhances the role of SSCP in advancements towards sustainability, whereas predictive analytics directly promotes sustainability, in addition to its contribution to increasing resilience.

This confirms the results of (Bag & Pretorius, 2022; Ivanov et al., 2019) who highlighted the non-direct outcomes of analytics through an improved adaptability of the supply chain. Industry 4.0-related technologies have direct ($\beta = 0.075$, $p = 0.020$) and indirect (I4.0I -SCR: $\beta = 0.064$, $p = 0.024$) effects on SSCP and enhance the mediated relationship. This follows (Raj et al., 2020; Wamba et al., 2017), which mentioned resilience as a highly important process in which digital transformation can lead to sustainability. The findings are in line with the Dynamic Capabilities View (Teece et al., 1997), where it is argued that companies using high-technology tools such as ADPA and I4.0I are capable of dynamically restructuring their abilities (e.g., resilience) to react to turbulence and meet their long-term sustainable objectives.

Table 13: Results of Hypothesis Evaluation

Hypothesis	Effect of	Effect on	*β*	*p*	Result
H1	I4.0I	AIDPA	0.056	0.000	Accepted
H2	I4.0I	SCR	0.064	0.024	Accepted
H3	I4.0I	SSCP	0.075	0.020	Accepted
H4	AIDPA	SSCP	0.087	0.042	Accepted
H5	AIDPA	SCR	0.053	0.000	Accepted
H6	SCR	SSCP	0.083	0.000	Accepted
H7a	I4.0I	SCR+SSCP	0.030	0.000	Accepted
H7b	AIDPA	SCR+SSCP	0.054	0.050	Accepted
Control Variable					
	Company Size	SSCP	0.112	0.868	Not Significant

Source: Authors own work

The structural model furnished most of the useful details that are in line with the overall objectives of the study. The strength of the variance of the dependent constructs by the independent variables is indicated by the coefficient of determination (R^2). As indicated in Table 14, (R^2) is 0.289, AI-driven Predictive Analytics (AIPA), 0.415, Sustainable Supply Chain Performance (SSCP) and 0.466, Supply Chain Resilience (SCR). (Hair, Joseph F. "Partial Least Squares Structural Equation Modeling," 2022) suggested it to be a relatively large degree of variance explanation in behavioral research; it means any values above 0.26 indicate that a model exerts a moderate to high power of explanation.

Likewise, the (Q^2) scores that determine the predictive relevance of the variables using the blindfolding processes are 0.278 (AIPA), 0.183 (SSCP) and 0.203 (SCR). These positive values affirm that the model does predict all the given endogenous constructs with matters of accuracy (Marcoulides,2013).

Table 14: Coefficient of variation (R^2) and Predictive relevance (Q^2)

Constructs	R-square	Q^2predict
AIDPA	0.289	0.278
SSCP	0.415	0.183
SCR	0.466	0.203

Source: Authors own work

Also, Table 15 indicates the effect size (f^2) provides more detailed information about individual paths strengths. The effect of AIDPA on SCR (f^2 = 0.470) is huge, and in this case, AI has played an enormous role in establishing resilience. Conversely, the impact of AIPA on SSCP (f^2 = 0.028) is rather minor yet significant, implying that the former plays a limited yet facilitating role in the development of sustainability. The size of the Industry 4.0 Integration-AIDPA effect (f^2=0.406) is also substantial, which also confirms the assumption that Industry 4.0 is a digital infrastructure that enhances the AI potential (Ivanov & Dolgui,2021). At the same time, the introduction of Industry 4.0 Integration into SSCP (f^2= 0.036) and SCR (f^2= 0.028) will have a small effect, which means that they will have an indirect effect mainly through AI. Lastly, the medium-range effect of SSCP on SCR (f^2= 0.145) indicates that the hypothesis that sustainability practices further deliver and consolidate supply chain resilience is also true (Ghadge et al., 2012).

Table 15: Effect Size (f^2)

Constructs	AIDPA	SSCP	I4.0I	SCR
AIDPA		0.026		0.470
SSCP				
I4.0I	0.406	0.036		0.028
SCR		0.145		

Source: Authors own work

5.4 Rival Model and Robustness Test

As an additional measure taken to evaluate the strength of the proposed research framework, the rival model analysis has been performed. Testing of rival models is usually suggested in structural equation modeling research to identify whether other model specifications are more explanatory than proposed theoretical model (Hair et al., 2022). These comparisons can be used to test the factual soundness of the conceptual model and make sure that other structures cannot be used to explain the proposed relationships better. In the proposed conceptual model, supply chain resilience (SCR) is placed as a mediating dynamic capability that exists between digital capabilities, which are AI-based predictive analytics (AIDPA) and Industry 4.0 integration, (I4.0I), and sustainable supply chain performance (SSCP). To test the strength of this assumption, some other competitor model was analyzed whereby the mediating role of SCR was omitted and the independent variables were directly correlated to SSCP.

Comparison of the suggested model with the rival model shows that the proposed one is stronger in explaining, which is represented by the values of the coefficient of determination (R^2) which is obtained using the structural model. To be more specific, the proposed model explained 41.5 percent of the variation in sustainable supply chain performance ($R^2 = 0.415$) and 46.6 percent of the variation in supply chain resilience ($R^2 = 0.466$). Based on the information given by (Hair et al., 2022), the values represent a moderate to high degree of explanatory power in behavioral research models.

These results indicate that the addition of supply chain resilience as an intervening capability has a major impact in enhancing the explanatory power of the model, which is treated as a logical result based on the thinking of Dynamic Capabilities View (Teece et al., 1997). Thus, the offered structural model is deemed more theoretically and empirically strong than the competing one, which proves the significance of resilience as one of the central processes via which digital capabilities generate sustainable supply chain performance.

As shown in Figure 2, the conceptual framework becomes validated following SEM analysis after all the p-values are less than 0.05, which implies that all the hypotheses are accepted.

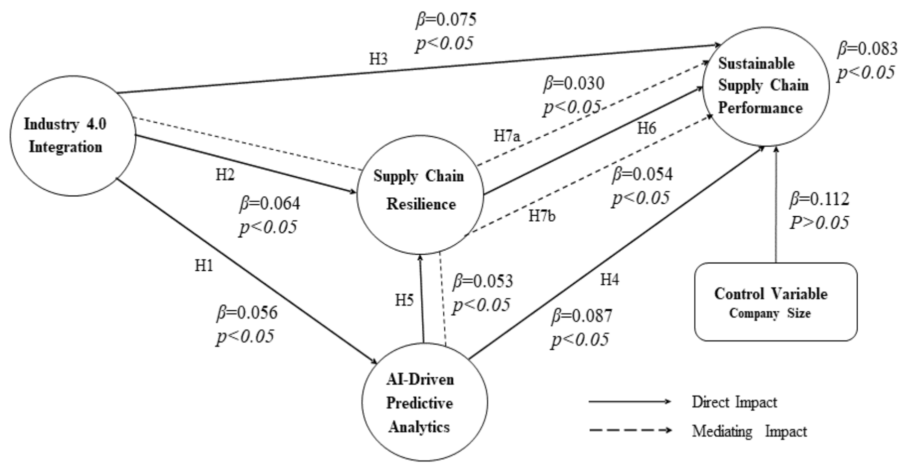

Figure 2: Final Results of Hypothesis Evaluation (Source: Authors own work)

6. Discussion

The present-day realities of a multi-dimensional and vast global context not only depend on the efficiency of operations, but also on strategic elasticity, resilience and sustainability in the context of enhancing supply chain effectiveness. Previous studies have emphasized the role of digitalization, AI-driven analytics, and Industry 4.0 in enhancing supply chain resilience (Ghanbari et al., 2025). Digital transformation (particularly, the use of AI-driven predictive analytics (AIDPA) and the implementation of Industry 4.0 (I4.0I) has emerged as an effective enabler of such features. Out of these, the supply chain collaboration, visibility and intelligent decision-making have been in the hottest focus to attain competitive advantage. Along supply chains, as complex technologies continue to spread, the incorporation of predictive analytics and cyber-physical systems is redefining disruption expectations in firms, changing response, and enhancing resilience and supply chain sustainability (Dubey et al., 2019; Ivanov et al., 2019). The paper studies the implications of AIDPA and I4.0 integration with regard to the resilience of supply chains (SCR) and sustainable supply chain performance (SSCP), putting focus on the SCR as a dynamic capability as a mediator of the impacts. This research contrasts the traditional perspectives that single out resilience as a standalone entity by building an organizational perspective around the concept of SCR as a strategic enabler of realizing the digital capabilities into sustainable results. The research is based on Dynamic Capabilities View (DCV) which represents a potent perspective to comprehend the process of company adjustment, integration, and transformation of internal and external competencies to respond to the faster-changing demands (Teece et al., 1997; Wamba et al., 2017).

The conception model was achieved owing to a strict literature review and its suitability with the Dynamic Capabilities Framework. AIDPA and I4.0I Integration were chosen as the independent constructs due to demonstrated contributions to empowering organizational agility, flexibility, and forecasting capabilities (Dubey et al., 201). The mediating variable, SCR has been introduced due to its central place in the transformation of technology capabilities to long-term value (Choi et al., 2018; Ivanov et al., 2019).The dependent variable, SSCP was utilized because of the rising global attention on the shift of supply chain sustainability (Jabbour et al., 2019). The validated measurement scales of literature were used to operationalize each construct as well. As an example, AIDPA was covered with questions by Wamba et al. (2020), and I4.0I was taken over by (Frank et al., 2019).Scales SCR and SSCP were modified after (Bag & Pretorius, 2022; Raj et al., 2020). A theoretically based and empirically testable structural model was made possible by the combination of these constructs. For that purpose, we stated two research questions (RQs).

To address the first research question, we have investigated the contribution of (AIDPA) and (I4.0I) integration on (SCR) and (SSCP), besides focusing on the mediating role of SCR. Six hypotheses of direct effects were used to answer the question. Based on the Dynamic Capabilities View (Teece, 2007; Wamba et al., 2017) the study determines the impact of AI-driven predictive analytics (AIDPA) and integration with Industry 4.0 (I4.0I) on supply chain resilience (SCR) and sustainable supply chain performance (SSCP), whereby SCR is the mediating factor. The first hypothesis, H1, has been supported, and that is, I4.0 integration can be very useful in improving AIDPA by offering the kind of digital infrastructure needed, including IoT, cloud computing, and cyber-physical systems, to make intelligent decisions and track analytics in real-time (Frank et al., 2019) .H2 confirms that I4.0I Integration positively affects SCR since I4.0I opens opportunities to experience data-driven analysis and reactiveness during disruption scenarios (Frank et al., 2019; Jabbour et al., 2019) and H3 confirms the direct influence of I4.0I on SSCP ($\beta = 0.075$, $p < 0.05$) in being able to achieve economic, environmental, social and resource utilization efficiency (Raj et al., 2020).H4 is supported because it confirms that ADPA has a positive impact on SSCP ($\beta = 0.087$, p = < 0.05), is supportive of sustainability by enhancing forecasting, waste loss reduction, and optimization of operations (Bag et al., 2020; Dubey et al., 2019). The H5 indicates that AIDPA positively affects SCR ($\beta = 0.053$, $p < 0.05$) through its ability to support proactive mitigation of risk and smart planning (Choi et al., 2018; Ivanov et al., 2019).H6 has determined that SCR is in direct support of SSCP, which articulates the idea that resilient systems provide continuity as far as operations are concerned and enable sustainability practices (Ivanov et al., 2019). Moreover, H7a and H7b indicate that SCR shall to a fundamental degree, shape the AIDPA-SSCP relationship, as well as the I4.0I-SSCP relationship, which is evidence of its strategic relevance in the conversion of digital capabilities into sustainable performance (Raj et al., 2020; Teece et al., 1997).On the whole, the paper performs an empirical verification of the fact that the digital change with the help of a resilient supply chain can be an effective tool in the practice of reaching sustainability, particularly in the context of resource-limited, volatile areas.

Hypotheses H7a and H7b were used to test the second research question. Hypothesis H7b revealed that SCR is the main mediator in the connection between AIDPA and SSCP, which means that predictive analytics can influence sustainability mostly because of its influence on resilience competence. This result strengthens the view of dynamic capabilities theory that resilience should provide an operational intermediary that is transformative to turn digital knowledge into sustainable operating to a sustainable action (Teece et al., 1997; Wamba et al., 2017). Hypothesis H7a also supported the mediating effect of SCR on the linkage between I4.0I and SSCP. These mediated effects reflect the strategic significance of SCR as a protective cushion and a transformative capacity to empower organizations to be able to adapt digital options to support sustainable results (Ivanov et al., 2019; Raj et al., 2020).

Overall, the two research questions were answered positively with the statistical justification of the 7 hypotheses giving solid empirical support that digital transformation, when diverted through sustainable supply chains, is of immense value to achieve the development of sustainability in resource-constrained, volatile conditions, such as the case of Bangladesh.

6.1 Implications for theory

The present study made a number of theoretical contributions to the fields of Dynamic Capabilities View (DCV), AIDPA, I4.0I, SCR, and SSCP. First, this study builds and elaborates the DCV by using an empirical example of how the synergistic combination of the AIDPA and I4.0I technologies results in dynamic capabilities that enhance the SCR and lead to sustainable supply chains' accomplishments. Traditionally, DCV focuses on the capacity of the organization to recombine both internal and external competencies in reacting towards the changes in the environment (Teece, 2007). Nevertheless, this paper goes a step further to reveal how integration of AIDPA and I4.0I produces adaptive learning loops and predictive intelligence to improve organizational outcomes of resilience and sustainability in turbulent situations (Ivanov, Dolgui, et al., 2016b; Wamba et al., 2020).

Second, the research indicates that the relationship between AIDPA and I4.0I and SSCP is empirically confirmed through SCR. There are smaller studies that have mainly analyzed resilience and sustainability as different outcomes or capacities (Bag et al., 2020). The current study consolidates them by displaying how resilience capacity, empowered by AIDPA and I4.0I becomes a channel through which the technological capacity flows to the occasion of sustainability. In this way, the study shows an answer to recent demands of discussing resilience not merely as a buffer of performance but as a proactive intermediary dynamic capability (Dubey et al., 2019; Queiroz et al., 2022). It enhances DCV through the perspective of resilience as an opportunity between digital innovation and sustainable transformation.

Third, this research adds to theoretical synthesis of AIDPA and I4.0I in the dynamic capabilities perspective, showing that they carry an overall and simultaneous effect on triple-bottom-line (TBL) dimensions- economic viability, environmental responsibility, and social equity. Another shortcoming is that past research on such technologies usually focuses on the relationship between them or does not consider their interactive possibilities (Bag & Pretorius, 2022; Frank et al., 2019). The superposition of the complementary dissimilarities of predictive analytics (AIDPA) and cyber-physical system (I4.0I) highlights the significance of the integrated digital strategy in the realization of formidable and sustainable supply chains. This coincides with new perceptions that digital transformation should be supported by capability-building so as to create sustained, sustainable value (Choi et al., 2018; Liu & Zhang, 2024).

Lastly, the study that is conducted is innovative because it is capable of installing an AI-enabled performance within a sustainable DCV-oriented model, thus providing a new theoretical perspective on any further research. It extends the sustainability research to the extent of focusing on how organizations can co-evolve resilience and use digital dynamic capabilities in the fast-changing environment.

6.2 Implications for practice

The study conducted sheds some practical implications concerning the supply chain (SC) managers and policymakers. The positive effect of AIDPA and I4.0I on SCR and SSCP highlighted in this paper is an indication to SC managers that digital transformation and the development of data-driven capabilities an urgent initiative that has to be done. The important factors that managers must consider to establish are the strong digital infrastructure to support analytics, a strong analytics workforce and the culture of data to drive proactive decisions. These disruptions can be better addressed by firms by using predictive technologies and I4.0I enablers, including IoT, automation, and using cloud-based platforms, to pursue the dual goals of managing them and contributing to sustainability (Bag & Pretorius, 2022; Wamba et al., 2017). Open innovation practices, including collaborative R&D, joint ventures, and knowledge-sharing platforms, significantly enhance the innovation capacity and sustainability of supply chains. By leveraging external knowledge sources and co-developing solutions with stakeholders, firms can accelerate technology adoption and improve their responsiveness to sustainability challenges (Holgersson et al., 2024).

The considerable mediating effect of SCR used in the study also means that resilience needs to be viewed as a strategic initiative by managers and not a response. The following forecasting and adjusting plans are required of them: scenario planning, visibility tool and cooperation with suppliers to develop the results of continuous sustainability, which in its turn, can presumably be based on the practices (Ivanov et al., 2019d; Raj et al., 2020b). The integration of those resiliency initiatives and those digital capabilities will guide organizations to sail through uncertainty without losing track of circularity. In addition, the synergistic nature of these two practices, AIDPA and I4.0I practices, requires cross-functional alignment of the companies. To ensure that predictive insights can be transformed into actionable, viable decisions across the entire supply chain, managers should encourage collaboration among the IT, operations and sustainability departments (Choi et al., 2018c; Liu & Zhang, 2024).

The current research will seek to establish the importance of marketing AIDPA and I4.0I that shall be adapted on an industry-wide basis to seek a change in the long-term image. Regulators can induce firms to invest in predictive analytics and sustainable behaviors in one way by offering them incentives through tax reliefs, grants, and opportunities to train. Governments can also facilitate the building of public-private partnerships and innovation hubs that support the exchange of knowledge and skills, upskilling, and the acquisition of digital skills within the supply chain context (Dubey et al., 2019; Teece, 2007).

In conclusion, only such businesses that can integrate both AIDPA and I4.0I in their operational and strategic logic can not only reinforce their disruptive resistance but also create a sustainable competitive advantage. Meanwhile, these advantages must be scaled to the larger supply chain system through task-coordinated policymaker assistance.

7. Conclusion

The paper formulated and empirically verified a theory based on the Dynamic Capabilities View (DCV) to discuss how the convergence of AI-Driven Predictive Analytics (AIDPA) and Industry 4.0 (I4.0) technologies helps increase the resilience of supply chains (SC) and advance their sustainable Performance. Relying on survey implementation with 194 supply chain leaders within the Bangladeshi Foods Manufacturing Industry, the results show that AIDPA has a substantial positive impact on enhancing the potential of firms to foresee, adjust and react to shocks. Moreover, together with the I4.0 capabilities (such as automation, IoT, and smart factory systems), these technologies contribute to the improvement of the operations in terms of flexibility and an approach to supply chain sustainability. The findings further indicate that supply chain resilience (SCR) is a decisive mediator amid AIDPA, I4.0 and sustainable performance. The identification of this finding highlights that technology adoption by firms is not a sufficient condition towards the achievement of long-term sustainability targets; rather, it should be actively established as a dynamic capability that allows adaptive learning, resource reconfiguration and fast recovery. By so doing, the current research will add to the body of literature that demonstrates how integrative approaches, which are complementary, of digital and organizational capabilities can result in excellent sustainable performance. Such wisdom is particularly applicable to companies that are subject to volatility and resource-limitation conditions, where the concepts of resilience have become strategic necessities.

7.1 Limitations and further research opportunities

Although the study provides great value to the researchers and practitioners in the field of food manufacturing, there are its limitations that can be explored in the future.

First, the study was cross-sectional, and it restricts the possibility of deducing the existence of causality among AIDPA, I4.0, SCR, and SSCP. In future research, it will be possible to rely on longitudinal or panel data to better represent the temporal development of these constructs (Dubey et al., 2019). Secondly, the paper entirely concentrates on food manufacturing industry in Bangladesh. The results might not be generalizable at other regional levels or food supply networks in the world, although this sector is crucial in food security of the nation and the number contributions to the economy. It is advised that the model be tested in other geographical locations or in other food producers across nations to increase its construct validity and applicability to the sector (Raj et al., 2020). Thirdly, single respondents by each firm were interviewed, with about half of them being the top-and mid-level managers in the supply chain. Although these professionals are a source of strategic information, it could be instructive to incorporate multi-stakeholder perspectives (e.g., operations managers, sustainability officers, and logistics providers) by interviewing them or adopting mixed-method designs since it advances the quality of findings and promotes the strength of the conclusions (Wamba et al., 2017). Fourth, although AIDPA and I4.0 were at the center of this study, other new technologies within the food supply chains could be discussed in future research. As an example, blockchain may enhance food traceability, making products authentic and consumers secure (Dwivedi et al., 2023). Similarly, other higher-level applications of AI, e.g. computer vision to detect quality, robotics to drive automation and even digital twins to predictive maintenance, can improve food safety and help to minimize food waste (Dubey et al., 2020; Wamba et al., 2017). IoT (Internet of Things) and edge computing have a large potential in terms of real-time monitoring of cold chains and temperature-sensitive logistics as well. Fifth, incorporating game-theoretic approaches into green supply chain design allows organizations to balance competitive and cooperative dynamics effectively.

Finally, the scholars can complement the theoretical findings through other theories like Organizational Learning Theory or Contingency Theory to comprehend how food production companies match capabilities with regulatory forces, sustainability priorities, and consumer trends in a fast-developing market environment.

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