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TECHNOLOGICAL INNOVATIONS ADOPTED FOR SUPPLY CHAIN IMPROVEMENT IN MANUFACTURING SECTOR AND ITS IMPACT ON FIRM PERFORMANCE: AN EMPIRICAL ANALYSIS

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Abstract
The acceptance of technological innovation is rapidly changing supply-chain management (SCM) and enhancing the performance of the firms in the manufacturing industry. This paper examined how various technological drivers such as a blockchain-based traceability, collaborative new-product development, human-computer-interaction (HCI) to provide AI, manufacturing servitization, re-distributed manufacturing, SCM improvement practices, and SCM innovation to risk management have impacted the performance of firms. The predictive structural model was tested based on the Dynamic Capabilities Theory and the Technology Acceptance Model (TAM) on survey data gathered on senior practitioners working in the supply-chain industry (n=442). The article discovered that all seven of them had a significant and positive contribution to firm performance. The HCI and SCM innovation are the most influential predictors, which are risk management and AI adoption respectively. The study contributes greatly because it integrates various technological constructs into one framework and contributes to the literature on the digitalization of SCM. The research also mixes macro-level dynamic capabilities with micro-level technology acceptance view; and also shows a high level of predictive power of tested model with PLS-SEM. The results emphasized that companies need to use a portfolio approach to technological innovation, giving preference to AI systems designed as user-centered, blockchain to promote transparency, collaboration to make predictions, and innovative risk-management solutions.

Keywords: Supply-chain innovation, Blockchain, AI adoption, Human–computer interaction, Servitization, Re-distributed manufacturing, Risk management, Firm performance, PLS-SEM

1. Introduction

Within the current business environment, the manufacturing industries are facing more challenges and opportunities than ever due to globalization, volatile demand, technology shocks, and sustainability. The supply chains have now become the backbone of manufacturing competitiveness and effective management of these chains is essential to gain cost efficiency, responsiveness and resilience. In trying to keep up with market changes and the unexpected disruptive factors, the traditional supply chain models also fail. Consequently, technological progress has become an important element in the area of supply chain improvement - which assists companies in achieving superior performance results (Ivanov and Dolgui, 2021). New technologies such as the Internet of Things (IoT), artificial intelligence (AI), blockchain, big data analytics, cloud computing and advanced robotics have entirely changed how the supply chain functions. These technologies provide greater visibility of the work, greater accuracy in forecasting, business process automation, and collaboration across the value chain. For example, IoT-sensors can be used for tracing the goods in real time, while AI-based algorithms can be used for planning the production and forecasting demand. Blockchain technology with its decentralized ledger helps to increase the transparency and confidence level of transactions (Queiroz et al., 2022). When combined together, these innovations minimize inefficiencies, improve resilience and increase competitiveness within manufacturing supply chains.

Technological innovation and the relationship with firm performance have been a popular research field but empirical studies on the relationship between the two in the manufacturing supply chain improvement remain in development. Companies using digital supply chain technologies frequently experience positive changes in financial results, operational efficiency, and performance in the area of innovation (Li, Tang, and Zhang, 2023). To illustrate, digital platforms allow making decisions faster, lead times are minimized, and the disruptions are minimized, which makes the customer satisfaction and profitability better. Furthermore, the innovations aimed at sustainability like green supply chain technologies are both environmental impact-reducing and reputational and economic enhancing (Tseng et al., 2022). The independent variable used in the current paper is technological inventions adopted in the supply chains and the dependent variable is the performance of the firm in the manufacturing sector. The study aims at bridging the gaps between theory and practicality by conducting an analysis empirically on how digital transformation initiatives translate into quantifiable positive organizational outcomes. This is necessary to recommend viable insights to the managers, policy makers and researchers. To decrease risks and ensure continuity, manufacturer's tendency shifted towards digital twins, traceability systems based on blockchains and distributed manufacturing models (Liu et al., 2022). These trends suggest a rethink of the application of technology, not as a way to improve operations, but as a long-term strategy to stay competitive. The present study examines technological development used in improving a supply chain in the manufacturing industry and examines the changes on the firm performance. This research will help not only in contributing to academic literature but also in managerial practice by combining both the theoretical bases as well as the empirical validation of the research work performed by several other researchers.

2. Literature Review

2.1 Theoretical background

The technological developments have been put at the forefront of enhancing the effectiveness of supply chain (SC) particularly in manufacturing industry where effectiveness, responsiveness and resilience have direct effects on the performance of firms. Analytic algorithms like artificial intelligence (AI), blockchain, Internet of Things (IoT), and big data analytics are all examples of technologies that are being used as strategic assets to facilitate supply chain agility, visibility, and coordination. As recent research has suggested, digital technologies have the great potential to enhance the operation performance by integrating the processes and predicting the decisions (Choi and Guo, 2022; Li, Tang, and Zhang, 2023). As such, technological adoption has a transformational effect on SC capabilities that can be observed in terms of performance benefits at the firm level in the form of lower costs, higher product quality and faster delivery. Recent findings highlight the importance of creating with AI-based analytics, digital twins and cloud computing, manufacturers have the power to realize supply chain resiliency by reducing demand variability, exploiting new opportunities, as well as transforming the operations in the supply chain (Wang, Xu, and Zhang, 2022; Liu et al., 2023). Big data analytics will pave the way for predictive demand planning and inventory optimization while blockchain will ensure secure transactions as well as supply chain visibility (Kshetri, 2021). Furthermore, IoT and cyber-physical systems can provide real-time visibility, which is also a case for better coordination in organizations and reducing some of the risks experienced with supply chains (Sun and Liu, 2022). Research also maintains that companies adopting these technologies can blame their companies' quantifiable gains in company efficiencies, flexibility, and overall firm performances (Zhang, Tang, and Yu, 2023).

2.2 Organizational Factors

Organizational issues are very instrumental in the effective implementation of technological innovations in supply chain (SC) improvement and the resulting effects on the firm performance. Leadership dedication and coherent strategy play a major role in the prioritization and integration of such technologies into supply chain operations as AI, IoT, and blockchain as a way to allow companies to increase visibility, efficiency, and resilience (Li, Tang, and Zhang, 2023). In addition, the research suggests that companies that have robust dynamic capabilities, i.e. the ability to sense, seize, and reconfigure resources have a better chance to make use of technological innovations to respond to environmental uncertainty and disruption leading to superior performance in the supply chain and finance (Teece, 2007; Liu, Sun, and Wang, 2023).

In addition, the orientation towards collaboration as well as the governance systems, i.e., good data governance and cybersecurity measures, are necessary in order to optimally leverage the opportunities and minimize the threats with regard to digital supply chains (Kshetri, 2021; Ivanov and Dolgui, 2021). It is also experimentally demonstrated that these organizational factors not only facilitate technological innovation adoption, but mediate and moderate it on the firms' performance through supply chain agility, integration, and resilience (Bhatia and Kumar, 2024; Chen, Yu and Li, 2023). As a result, organizational preparedness, organizational capabilities and culture play a critical role as a foundation for manufacturing companies to successfully incorporate technological innovations for enhancing supply chain performance and obtaining sustainable performances.

2.3 Technological Factors

The technological factors play an essential role in the transformation of supply chain (SC) in the manufacturing industry and directly affect the performance of firms. Due to the implementation of more sophisticated digital technologies, like big data analytics (BDA), artificial intelligence (AI), Internet of Things (IoT), blockchain, cloud computing, and digital twins, the processes of the supply chain have been re-conceptualized in terms of greater visibility, responsiveness, and coordination. The IoT-based systems also improve real-time monitoring of materials and product, which improve the traceability and minimise the risk in operations (Huang and Li, 2023). In the same way, blockchain technology facilitates open and secure information sharing between SC partners, which promotes trust and reduces the risk of fraud and compliance concerns (Queiroz and Fosso Wamba, 2022).

Cloud-based systems and digital twins go even further to enhance supply chain flexibility and resilience with the ability to include real-time data and simulation to enable firms to predict disruption and optimize production time schedules (Wang, Xu, and Zhang, 2022; Liu, Sun, and Wang, 2023). The technologies not only enhance the integration of the supply chain, but also, they increase the agility of firms and their innovation potential, which improves their overall performance. Recent surveys endorse that companies that use digital technologies have better operational and financial results due to the decreased lead times, better quality of the product, and higher customer satisfaction (Li, Tang, and Zhang, 2023; Bhatia and Kumar, 2024). Furthermore, the adoption of green and sustainable technologies in the context of supplying chains, also relates to the performance of firms by enhancing the decrease of environmental effects as well as meeting the requirements of the regulatory and stakeholder perspectives (Chen, Yu, and Li, 2023). In the best way, firms will be able to adjust to changing market needs and disruptions by implementing modular and interoperable solutions (Sun and Liu, 2022). On the whole, the technological factors are the basis of the digitalization of the manufacturing sector supply chain with the evident data that their integration improves the ability of supply chains and provides quantifiable benefits in the performance of firms.

2.4 External Factors

The external factors are an important influence on the adoption of technological innovations in the supply chains and determine the ultimate effect that they have on the performance of the firm. The level of competition pushes manufacturing companies to make investments in digital technologies, including blockchain, big data analytics, and IoT, to make the company more visible, cost-effective, and responsive, thus, delivering high-performance results (Queiroz and Fosso Wamba, 2022; Li, Tang, and Zhang, 2023). Another force that is increasing adoption is government incentives and regulatory requirements because they lead to transparency, traceability, and sustainability in supply chains, especially in the sectors that have environmental and quality compliance (Chen, Yu, and Li, 2023). External drivers are also the customer and market demands. The growing customer demand towards speed, tailoring, and sustainability motivate companies to implement digital solutions to support the real-time monitoring, predictive planning, and environmentally sustainable business (Huang and Li, 2023). In addition, the supply chain innovation is quite frequently dependent on the technological maturity of partners and industry ecosystems. The cooperation between suppliers and logistics providers will also support the exchange of data, interoperability, and the collective implementation of technologies (cloud-based and blockchain) to increase the integration and performance of the entire supply chain (Wang, Xu, and Zhang, 2022). On the other hand, the lack of alignment among digital maturity of partners may restrict the fulfilment of anticipated benefits (Sun and Liu, 2022). In general, external forces, which are competition, regulation, customer pressure, partner preparedness, and environmental turbulence, do not only moderate the rate and extent of technological adoption but also define the extent of the technological adoption into supply chain enhancement and firm performance.

2.5 Financial Performance

One of the key outcome variables in research on technological innovation adoption as a means of improving the supply chain (SC) in the manufacturing industry is financial performance. Increased transparency and traceability, reduced costs of transactions, less fraud, and compliance, which are the benefits of blockchain and IoT technologies, support the financial performance by decreasing risk exposure and preserving brand value (Queiroz and Fosso Wamba, 2022; Huang and Li, 2023). Additionally, online simulators and cloud computing also allow manufacturers to model disruptions, to streamline production schedules, and to optimize the logistics networks, making operations more efficient and have a positive impact on margins (Wang, Xu, and Zhang, 2022; Liu, Sun, and Wang, 2023). The available evidence proves that the companies that take a strategic initiative and invest in SC digitalization achieve better results in profits and in the presence of their niche in the market than their competitors (Bhatia and Kumar, 2024). Innovations that are sustainable also have a dual role in performance in terms of financial performance. Green supply chain technologies help to cut waste and decrease energy use, but also increase profitability in the long-term perspective by improving the corporate image and compliance with regulations (Chen, Yu, and Li, 2023). All in all, the financial performance is an important measure of the effectiveness of technological innovations in converting SC improvements into the actual economic benefit, which confirms their strategic significance in the manufacturing process.

2.6 Innovation Performance

The role of innovation in terms of performance is considered as one of the key components in companies' performance, especially in manufacturing industries, where technological innovations in supply chains have triggered the development of new product, process, and business models. Another result of digitization is that the use of digital technologies, such as artificial intelligence (AI), big data analytics (BDA), blockchain, and the IoT, results in increased knowledge creation, collaboration, and decision making across supply chain partners (Choi and Guo, 2022; Li, Tang and Zhang, 2023), all of which increase organizational innovation. It is proposed that digital supply chain integration leads to product and process innovation, allowing real-time data sharing and analytics-based insights to speed up the product development process and enhance customization (Huang and Li, 2023). In the same way, the use of blockchains promotes credibility and cooperation between supply chain participants and establishes the environment in which partnership-based innovation efforts are possible (Queiroz and Fosso Wamba, 2022). The Dynamic Capabilities Theory (DCT) also clarifies the reason why companies that perceive the change of the market and adopt technological changes are more inclined to innovate within the changing environment (Teece, 2007; Liu, Sun, and Wang, 2023). Empirical research points out to the fact that manufacturing companies that capitalize on the use of digital technologies have a better innovation performance due to the introduction of environmentally-friendly practices, design flexibility, and the exploration of new service model (Chen, Yu, and Li, 2023; Bhatia and Kumar, 2024). In addition, green product and process innovation is catalyzed by sustainable technological innovations that go beyond enhancing environmental performance to provide the competitive capability of the organization in the long term. In general, innovation performance is an important mediating variable in supply chain digitalization, as it connects the use of technologies to the improvement of financial and operation performance in manufacturing companies.

2.7 Re distributed manufacturing and adoption for supply chain improvement

Re-distributed manufacturing has become a noticeable concept as a new form of supply chain (SC) design, which allows decentralizing production and manufacturing nearer to demand markets. RDM relies on the use of advanced technologies, including additive manufacturing, digital twins, cloud-based platforms, IoT-enabled systems, and so forth, to build flexible, localized, and customer-centered supply networks, in contrast to traditional centralized manufacturing (Srai and Harrington, 2021). This will not only reduce lead times and logistics spending, but will also make the supply chain more resilient by reducing the breakdowns associated with global dependencies (Ivanov & Dolgui, 2021). Digital technologies are a huge motivator to the adoption of RDM. AM facilitates quick prototyping and local opportunities for production means that mass customization possibilities are possible, also the rates of inventories should be lower (Khajavi et al., 2022). Cloud-based manufacturing platforms and digital platforms have enabled promoting the coordination work of geographically dispersed facilities, while ensuring the real-time visibility and synchronization of the supply chain (Xu, Xu, and Li, 2022). Regarding environmental and sustainability considerations, RDM has a role to play in green supply chain management in terms of reducing transportation distances, carbon footprints, and facilitating the use of the circular economy, e.g. localised remanufacturing and recycling (Srai et al. 2022). Additionally, making use of RDM also improves innovation's performance through the experimentation based on design flexibility, product customization, and joint R&D (Bhatia and Kumar, 2024). All in all, re-distributed manufacturing adoption gives a paradigm shift to manufacturing supply chains, providing a chance to enhance agility, resiliency, sustainability, and customer-centricity. It is one of the enablers to future-ready supply chain strategies in an ever-volatile and digitalized global environment.

2.8 Supply chain innovation for risk management & competitive advantage and adoption for supply chain improvement

The concept of supply chain innovation (SCI) has become a strategic reaction to the rising market instability, global shocks and the need to be more resilient and competitive. SCI focuses on the merging of contemporary technologies, innovative processes and collaborative practices that enhance flexibility, visibility and responsiveness of the supply networks (Wamba et al., 2022). In the terms of risk management, blockchain, big data analytics, artificial intelligence (AI), and digital twins are innovations that enhance the visibility of the supply chain and predictive power, enabling companies to anticipate disruptions and create proactive mitigation solutions (Ivanov & Dolgui, 2021; Choi and Guo, 2022). SCI enhances the sustainability measures, where energy-efficient logistic and environmentally-friendly manufacturing, not only contribute to the minimisation of the environmental risks, but also improves brand image and competitiveness in future (Chen, Yu, and Li, 2023). Research highlights the importance of leadership commitment and cross-supply chain partner collaboration, as well as governance mechanisms to facilitate the management of the data privacy and interoperability issues in successful SCI adoption (Queiroz and Fosso Wamba, 2022; Bhatia and Kumar, 2024). Finally, SCI adoption enhances supply chain resilience, minimizes risks, and offers competitive advantage, which places firms in turbulent business settings to emerge successfully in the business industry, as well as attaining high-quality operational and financial performance.

2.9 Collaborative new product development with forecast & resource sharing and adoption for supply chain improvement

New product development has emerged as a crucial supply chain enhancement factor because more and more companies are seeking to use inter-organizational collaboration, sharing of resources and integrating information to help them reduce the length of product life cycles and to react to ever-changing market pressures. Supply chain partners can promote their decision-making process, minimize uncertainties, and make sure that the innovation processes correspond with demand needs and operational capabilities (Zhang and Yu, 2020). Collaborative forecasting is a decision support system that utilizes real-time data and predictive analytics to optimize demand planning and production scheduling for reducing the bullwhip effect and improving supply chain agility (Liu et al. 2021). In terms of resources sharing, collaboration allows organizations to share knowledge, technological capabilities and financial funds which allows the quicker innovative process and reduces cost of development (Sun and Liu, 2022). This is further supported by cloud-based systems and other digital ecosystems, which help in co-designing products between partners, publishing digital prototypes, and real-time feedback on the products from customer-supplier collaborations (Huang and Li, 2023). The type of collaboration not only brings faster time to market proportion but also affects the enhancement of product quality and flexibility which makes the firms to be in the dominance of the competitive landscape in the turbulent environment (Chen et al., 2021). Moreover, IoT and blockchain technologies used in participative platforms bring more level of transparency, protection of intellectual property and trustfulness among partners (Wang et al., 2022).

2.10 Manufacturing servitization via tam and adoption for supply chain improvement

Servitization in the manufacturing industry - the move towards providing products as integral product-service offerings, not just having to sell the product to the customer - has become a strategy in the betterment of the supply chain and the development of new sources of value. Recent research emphasizes that the effective implementation of a servitization is strictly interconnected with the use of digital technologies, including IoT, AI, and cloud platforms, which allow to monitor the business in real-time, predictive maintenance, and give customers customized services (Baines and Lightfoot, 2023). The perceived usefulness in the context of servitized supply chain has to do with the way digital service technologies can increase the efficiency in operations, minimize the downtime, and improve customer satisfaction. As an example, the IoT predictive maintenance enables to prolong the life cycles of products not only but also ensures the improved usage of resources in the supply networks (Kamalaldin et al., 2021). The perceived ease of use also has an impact on whether the employees and partners want to use service-oriented digital tools, including collaborative tools to remotely diagnose or process optimization via digital twins, which increases inter-firm coordination (Paschou et al., 2020). There are empirical studies indicating that the ease of use of digital systems makes them less resistant to change and increases the speed of the servitization change in manufacturing (Zheng et al., 2022). Servitization through the prism of TAM results in major improvements to the supply chains. The provision of value propositions based on the services leads to the creation of strong and long customer relationships, revenue stream stabilization, and increased resilience of the supply chain (Raddats et al., 2023). In addition, business models driven by services promote more intensive cooperation with suppliers and logistics companies, advance the ability to predict demand, distribute resources, and sustainability levels.

2.11 Human computer interaction framework for ai in logistics and adoption for supply chain improvement

Logistics: Application of Artificial Intelligence (AI) in logistics and supply chain management activities is transforming the way companies approach forecasting, routing, warehousing, and decision-making. By creating user intuitive interfaces, human operators and AI interactions in a human-like way, companies are able to reduce the cognitive load, reduce the errors, and optimize the decision-making process (Cai et al., 2022). According to the recent research, algorithmic accuracy and explainability and user confidence are required when implementing AI in logistics. AI familiarity: Explanable AI (XAI) is part of the HCI model, to develop the profession of supply chain people's understanding of AI-based recommendations on inventory placement, forecasting of demand and vehicle routing (Glikson and Woolley, 2020). There is transparency at this level and the users are confident and will not refuse to adopt it. In addition, user expertise and context-based adaptive interface will improve the perceived usefulness and ease of use, which are vital to successful technology assimilation (Sun et al., 2022). The HCI-powered AI applications have already made an impact on logistics by enhancing warehouse automation, dynamic routing and collaborative planning. For example, voice-based and augmented reality (AR) interfaces for workers to work more efficiently in warehouses, while managers can use AI-based systems to optimize the supply chains in real-time using interactive dashboards (Wamba et al., 2021). Experience suggests that the application of HCI concepts to the introduction of AI can facilitate the agility, responsiveness and resilience in the supply chain, which can contribute to better performance of firms. Finally, adopting AI through HCI system ensures that technology complements human knowledge, which leads to more successful supply chain optimisation and competitive advantage.

2.12 Supply chain improvement in manufacturing sector

Due to globalization, digitalization, and growing demand to be resilient and sustainable, the research literature and laboratory practices in the manufacturing industry have shifted sharply towards the improvement of supply chains. The strategies of cost efficiency, operational flexibility, visibility, collaboration, and risk mitigation should be implemented to improve supply chain (Ivanov and Dolgui, 2021). The supply chains of the manufacturing industry have been revolutionized by the continuous creation of additional technologies such as the Internet of Things (IoT), big data analytics, blockchain, and artificial intelligence (AI) that can deliver a real-time monitoring network, predictability, and automation (Queiroz et al., 2022). The supply chain is in the focus of improvement through the digital transformation. IoT and AI can increase demand forecasting and production planning and optimization precision, cut down on lead time, and strengthen sensitivity to the change of the market environment (Li et al., 2023). Blockchain makes the transactions secure and unchangeable, resulting in better transparency and trust in the network of supply chain in quality-sensitive industries (Saberi et al., 2019). Moreover, the cloud platforms offer the ability of collaborative resource planning and sharing among partners which provides better integration and agility (Kohtamaki et al., 2020). Digital and adaptive strategies such as multi-sourcing, digital twin, and distributed manufacturing are recommended by the research to be more resilient and have a competitive advantage in the long term (Liu et al., 2022). Sustainability has become a driving force too, and the implementation of green supply chain practices can not only increase environmental performance but also a better reputation and operational efficiency of a firm (Tseng et al., 2022).

2.13 Blockchain based traceability system and adoption for supply chain improvement

Blockchain technology is gaining increasing attention as a disruptive supply chain management tool for the manufacturing industry. The issues which are traditionally faced by conventional supply chains are inefficiency, lack of transparency and information asymmetry in tracing the origin and flow of the products (Saberi et al., 2019). Blockchain is a decentralized, immutable database which can track product and transactions in real time without any manipulation or risking, and adds transparency and trust between different stakeholders (Casino et al., 2021). Traceability plays a significant role in the manufacturing supply chain; it's essential for product authenticity and quality control and for compliance. Blockchain systems can also provide end-to-end traceability as all the transactions, such as sourcing of raw materials, end-delivery, etc., are recorded on a decentralized register that reduces the risks of fraud and counterfeit goods as well as any issues with the supply chain (Wang et al. 2022). Artificial systems can also contribute to a sustainability practice, in the form of ethical sourcing and the reduction of the environmental impact by reporting transparent carbon footprint (Kouhizadeh et al., 2021). Blockchain traceability has been linked to the improved effectiveness and efficiency of the supply chain. Several studies show that the use of blockchains will increase the level of trust and coordination among the partners by providing non-manipulable documents and fosters cooperation and reduces conflicts (Manupati et al., 2020). Besides, the use of blockchain helps in ensuring the sustainability of a supply chain, as it can detect any interruption in the chain and maintain the chain by means of the transfer of data securely (Queiroz and Fosso Wamba, 2019). Despite these benefits there are still a number of barriers to adoption including the high costs of implementation, interoperability, and reluctance from legacy members of the supply chain (Treiblmaier, 2019). Therefore, blockchain is becoming an important technology innovation of supply chain enhancement, offering visibility, effectiveness, and durability to the manufacturing industry.

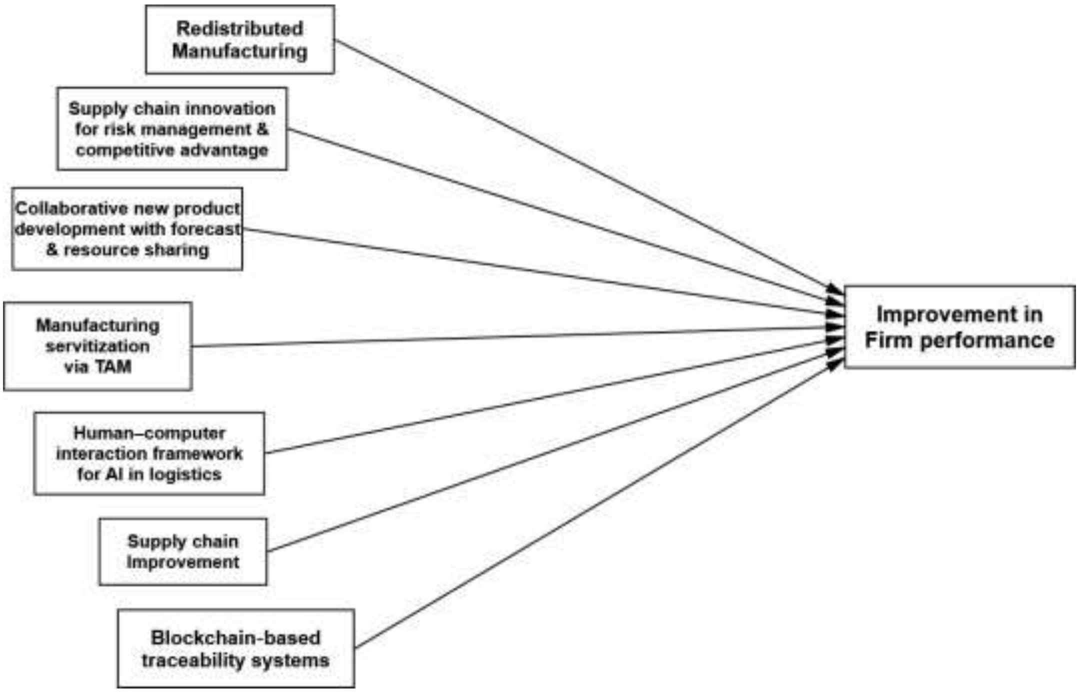

Figure. 1. Conceptual model for innovations in SCM

3. *Research methodology*

3.1 Research objective and design

This study examines the impact of different technological innovations adopted by the manufacturing firms for the purpose of improving supply chain management on the improvement in firm performance. The study identified seven different technological innovations in supply chain managements namely *Re-distributed manufacturing, collaborative new product development with forecast & resource sharing, human–computer interaction framework for AI in logistics, manufacturing servitization via TAM, supply.* These *technological* innovations in SCM were identified from the extensive literature review. A conceptual structural model was proposed indicating the influence of selected technological innovations and improvement in firm performance and examined the structural model using SEM-PLS approach. The study adopted the descriptive research design to arrive at the conclusions on the basis of hypothesis testing applied on the collected primary data.

3.2 Data type and sampling design

The primary responses were collected from 442 industry executives with more than 5 years of experience in supply chain management in the manufacturing firms and aware about the technological innovations in the area of supply chain management adopted by their firms in recent years. The responses were collected using a survey method, with the help of questionnaire developed for the purpose of data collection. A non-probability sampling method, *judgmental sampling* was adopted to collect primary responses from the selected industry executives. The questionnaire began with three criteria questions, the answer to which required respondents to give their answers to the other questions that included in the questionnaire. The questions based on the three criteria are asking whether the respondent was aware of the various technological innovations in supply Chian management (yes/no), how long they were involved with the implementation process of the technological innovations in the firms and their designations (junior, middle level, senior management) and the answers were required of the employees with middle level and senior management respectively. The respondents were selected in various phases. The list of manufacturing companies was first gathered using various sources like websites, reports etc. This is then succeeded by emailing requests to HR managers seeking their assistance in gathering the responses of the eligible employees in supply chain department. The top-level responses were gathered among the industry executives during a period of more than six months, between Nov 24 and April 25. A total of 442 complete responses were obtained within a period of six months and were taken into account in the final data analysis in order to test the hypothesis and as well as to attain the aim of the study. The questions were answered according to a 7 point scale (1 = strongly disagree, 2 = disagree, 3 = somewhat disagree, 4 = cannot say, 5 = somewhat agree, 6 = agree, 7 strongly agree) utilized in the questionnaire. The size of the sample 442 can be regarded as representative since this figure met the requirements of 10 times the number of items the structural model contained (Nunnally, J. C., and Bernstein, I. H., 1994).

3.3 Scale development and questionnaire design

The questionnaire employed in the research was formulated in various phases, with the step one beginning with the recognition of the various variables as stated in the conceptual framework under the elaborate literature review and the items to gauge these factors. The initial questionnaire was written with the determined factors and the items. The stage two incorporates the processes undertaken to ensure the content validity of the scale. The draft questionnaire was reviewed at this phase in terms of content validity using the assistance of senior industry executives who had over ten years of experience in managing technological advances in SCM within their respective firms and five academic professionals who had published research papers on the research problem. Based on the recommendations and considerations of the experts, the draft questionnaire was revised, thus, ensuring the content validity of the scale. The third phase involves the face validity testing done through pilot survey involving 59 industry respondents. Where reliability of responses, duplicity of items was studied as well as the descriptive analysis of answers etc. The pilot survey was useful in further refinement of the questionnaire by eliminating some statements, simplifying the wording of the statements etc. Lastly, the final data collection was done using the modified questionnaire among the respondents. The statements/ items in the questionnaire were modified based on the various studies.

3.4 Statistical methods

Various statistical techniques assisted in conducting the hypothesis testing by operating on the primary responses collected to realize the objectives of the research. The frequency distribution was also used on the responses to depict the sample demographics. Cronbach alpha was used to test the internal consistency of the factors that were included in the measurement scale. The confirmatory factor analysis (CFA) method was used to test the construct validity of the measurement scale in the research tool. The construct validity involves the analysis of the convergent and discriminant validity of the research instrument. The 'variance inflation factor (VIF) estimates were used to test the item multicollinearity of individual items in the scale. It was tested that the common method bias (CMB) was present in the responses with the help of Harman single factor method. Lastly, the hypothesis proposed was tested using SmartPLS software through the use of SEM-PLS approach. The choice of PLS-SEM approach in the study was explained by the fact that the proposed model is a completely new input to the literature. To determine the proposed model, the prediction orientation approach is better to use. The section that follows talks about the findings of the statistical analysis performed on the responses.

4. Data Analysis and Interpretation

This section discusses about the findings and interpretations of the statistical analysis applied in the study.

4.1 Structural equation modelling

The most important response data were examined with the help of PLS-SEM which analyzes and proves hypotheses and models suggested. SEM is a powerful methodology that may be employed in directly and indirectly comparing interactions among different constructs. SEM has had application in various fields within the social sciences like marketing, psychology, business, and education among others. In recent literature, the study of innovations in SCM has been done in various papers with the usage of SEM. SCM innovation is one of the relatively recent fields where the issue of the SCM impacts on firm performance is evaluated. Technological innovations in SEM describes the relationships that exist between innovations that have impacts on SCM performance in the changing business environment. It is important to analyse the measurement model to determine construct validity and reliability before analysing the interrelationships between the constructs included. Internal consistency, reliability, convergent and discriminant validity of the measurement model were investigated. The proposed hypothesised measurement model is tested by the PLS algorithm, the results of which are presented in the following sections. The SEM strategy used in this research agrees with technological advances in SCM by measuring the relationship among five constructs and enhancement of firm performance that were employed in this study. The relationships can be stretched to predictive models so as to predict the effects of innovations in SCM on the performance outcomes of firms so that actionable knowledge can be provided to supply chain decision-makers.

4.2 Reliability and validity analysis

In the research, Cronbach alpha was used to test the internal consistency reliability which is the correlation of two items that include the measurement of a construct and the level to which a group of items or a set of statements on a scale is consistent. The range of the Cronbach alpha value is between 0 and 1; nevertheless, it should have a greater value than 0.7. CFA method was used to test the construct validity of the measurement model where construct validity comprises of convergent and discriminant validity. Construct loadings, composite reliability and average variance extracted were used to determine convergent validity. The Fornell Larcker criteria was used to review discriminant validity. The outcome of the reliability and validity analyses are given in Table 1. A Cronbachs alpha of more than 0.7 is said to be acceptable with regard to Internal consistency and a value of 0.8 and above is said to be good. Cronbach alpha of the eight constructs obtained as reported in Table 1, with a range of 0.896 to 0.929, has indicated an excellent internal consistency reliability. The measures included were identified to be reliable, valid as well as able to be used in studies which are carried out using SEM analysis. Construction reliability Construction reliability is a measurement model that checks construct reliability and convergent validity. It evaluates the consistency of the construct, the stability and equivalence of the construct and provides a more retrospective measurement of overall reliability. A C.R. value bigger than 0.7 can be used to determine the presence of adequate scale validity.

Table 1 reveals the range of construct reliability values of between 0.896 and 0.928 indicating that the eight constructs were well-reliable. The convergent validity is the extent to which the items of the construct converge or have a substantial proportion of intersecting variance. Evaluation of convergent validity was made in standardised construct loadings. A construct should have standardised loadings greater than 0.50 in order to be regarded as valid. According to Table 1, the observed variables had a range of construct loading of between 0.639 and 0.883. Consequently, we can be sure that there is convergent validity. The discriminant validity of the scale depicts the lack of association of a construct with others. In the analysis of discriminant validity, the average variance extracted (AVE) estimates of each construct should be greater than the maximum shared variances of each specific construct and square root of AVE greater than construct to construct correlation. Table 4 shows that all of the constructs are weakly but positively correlated with one another, indicating that they are independent. The square roots of the AVE were greater than the non-diagonal associated values in all the constructs (bold values in Table 3). These results describe the high correlation of every construct with item of the construct. The discriminant validity of the measurement model was tested by HTMT ratio. The findings of the HTMT ratio are reported in table 4 wherein the estimated ratio of each pair of constructs was lower than the required value of 0.8. In this way, the findings confirm the discriminant validity of the measurement scale.

Common method bias (CMB)

CMB was also examined and reported after validating the internal consistency reliability and construct validity of the measurement scale to address potential biases that detailing how self-reporting bias was minimised. (i) The study examines Harman's single-factor test, which confirmed that no single factor explained more than 42.26% of the variance, ensuring that common method bias is unlikely to distort findings. According to the obtained values, the variance explained by a single factor was 42.26%, smaller than 50%. Thus, it can be concluded that the responses were clear from common method bias, and all the conclusions made in the study were free from bias (Table 5).

Table 1: Reliability and validity analysis

Construct	**Items**	**Mean (SD)**	**Standard factor**	**Cronbach's alpha**	**Composite reliability**	**Average variance**
Blockchain-based traceability systems	BBTS1	4.747	0.792	0.903	0.902	0.650
	BBTS2	4.579	0.854			
	BBTS3	4.629	0.824			
	BBTS4	4.690	0.784			
	BBTS5	4.729	0.774			
Collaborative new product development with forecast & resource	CNPD1	4.760	0.849	0.902	0.902	0.648
	CNDP2	4.82	0.795			
	CNPD3	4.790	0.825			
	CNPD4	4.740	0.817			
	CNPD5	4.692	0.737			
Human computer interaction framework for AI in logistics	HCI1	4.661	0.799	0.911	0.909	0.667
	HCI2	4.706	0.813			
	HCI3	4.812	0.760			
	HCI4	4.523	0.825			
	HCI5	4.652	0.883			
Improvement in firm performance	IFP1	4.774	0.755	0.900	0.902	0.570
	IFP2	4.473	0.639			
	IFP3	4.776	0.803			
	IFP4	4.692	0.755			
	IFP5	4.692	0.785			
	IFP6	4.731	0.784			

	IFP7	4.740	0.751			
Manufacturing Servitization via TAM	MSTAM1	4.351	0.870	0.929	0.928	0.722
	MSTAM2	4.269	0.835			
	MSTAM3	4.222	0.835			
	MSTAM4	4.195	0.862			
	MSTAM5	4.127	0.845			
Re-distributed manufacturing	RDM1	4.636	0.822	0.896	0.896	0.634
	RDM2	4.729	0.807			
	RDM3	4.615	0.837			
	RDM4	4.851	0.744			
	RDM5	4.778	0.766			
Supply chain innovation for risk management & competitive	RMCA1	4.577	0.760	0.899	0.899	0.641
	RMCA2	4.575	0.805			
	RMCA3	4.636	0.781			
	RMCA4	4.471	0.823			
	RMCA5	4.595	0.832			
Supply chain improvement	SCI1	4.785	0.744	0.912	0.911	0.563
	SCI2	4.839	0.722			
	SCI3	4.835	0.796			
	SCI4	4.903	0.738			
	SCI5	4.765	0.763			
	SCI6	4.817	0.675			
	SCI7	4.835	0.753			
	SCI8	4.817	0.804			

Table 2. Discriminant validity

	BBTS	**CNPD**	**HCI**	**IFP**	**MSTAM**	**RDM**	**RMCA**	**SCI**
Blockchain-Based Traceability Systems (BBTS)	**0.806**							
Collaborative New Product Development with Forecast & Resource Sharing (CNPD)	0.679	**0.805**						
Human–Computer Interaction Framework for AI in Logistics (HCI)	0.710	0.683	**0.817**					
Improvement in Firm Performance (IFP)	0.756	0.772	0.770	**0.755**				

Manufacturing Servitization via TAM (MSTAM)	0.703	0.736	0.738	0.749	**0.850**			
Re Distributed Manufacturing (RDM)	0.624	0.607	0.630	0.672	0.615	**0.796**		
Supply Chain Innovation for Risk Management & Competitive Advantage (RMCA)	0.422	0.452	0.394	0.574	0.405	0.267	**0.801**	
Supply Chain Improvement (SCI)	0.555	0.540	0.542	0.668	0.574	0.446	0.395	**0.750**

Table 3: Discriminant validity using HTMT (Heterotrait-monotrait)

	BBTS	**CNPD**	**HCI**	**IFP**	**MSTAM**	**RDM**	**RMCA**	**SCI**
Blockchain-Based Traceability Systems (BBTS)								
Collaborative New Product Development with Forecast & Resource Sharing (CNPD)	0.679							
Human–Computer Interaction Framework for AI in Logistics (HCI)	0.707	0.682						
Improvement in Firm Performance (IFP)	0.758	0.773	0.770					
Manufacturing Servitization via TAM (MSTAM)	0.703	0.738	0.736	0.752				

Re Distributed Manufacturing (RDM)	0.622	0.606	0.627	0.673	0.613			
Supply Chain Innovation for Risk Management & Competitive Advantage (RMCA)	0.421	0.449	0.392	0.572	0.404	0.266		
Supply Chain Improvement (SCI)	0.555	0.541	0.540	0.672	0.574	0.445	0.393	

Table 4 : Common method bias. Extraction method: Principal Component Analysis (PCA)

Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	19.015	42.255	42.255	19.015	42.255	42.255
2	3.095	6.877	49.132			
3	2.728	6.063	55.195			
4	1.744	3.876	59.071			
5	1.489	3.308	62.379			
6	1.372	3.049	65.429			
7	1.219	2.709	68.138			
8	1.096	2.435	70.572			
9	.797	1.772	72.344			
10	.744	1.653	73.998			
11	.594	1.320	75.318			
12	.552	1.227	76.545			
13	.519	1.154	77.699			
14	.503	1.119	78.817			
15	.489	1.086	79.904			
16	.463	1.028	80.932			
17	.451	1.002	81.934			
18	.447	.993	82.927			
19	.430	.955	83.882			
20	.421	.935	84.817			
21	.407	.904	85.721			
22	.398	.885	86.606			
23	.376	.835	87.441			
24	.362	.804	88.245			
25	.344	.764	89.009			
26	.333	.739	89.748			

27	.323	.717	90.465			
28	.311	.692	91.157			
29	.306	.680	91.837			
30	.287	.638	92.476			
31	.285	.633	93.108			
32	.276	.614	93.722			
33	.272	.605	94.326			
34	.264	.586	94.912			
35	.255	.567	95.479			
36	.250	.555	96.034			
37	.241	.536	96.569			
38	.228	.507	97.076			
39	.220	.488	97.564			
40	.213	.473	98.037			
41	.198	.439	98.476			
42	.188	.418	98.895			
43	.179	.398	99.292			
44	.169	.376	99.668			
45	.149	.332	100.000			

4.3 Structural model and hypothesis testing

The analyses of the hypothesized conceptual research model were carried out with the help of SEM in SMART PLS software. Fig. 2 presents the structural model, and Table 7 generalizes the results of the SEM analysis. Table 6 has a description of the estimated values of the endogenous constructs of standardized path coefficients (b), standard error, t-statistics, p-value and R-SQ. The level of significance(a) was fixed as $p < 0.05$. The results of the hypothesis testing can be seen in Table 6, where each of the beta coefficients gives an explanation of the relative value of the factor. The path coefficients were all positive. The seven selected elements, i.e., blockchain-based traceability, systems collaborative new product development, forecast and resource sharing, human-computer interaction structure of AI in logistics, manufacturing servitization through TAM, manufacturing re-distributed, supply chain improvement, supply chain innovation aimed at risk management and competitive advantage, all play an important role in improvement in firm performance. Human-computer interaction framework of AI in logistics holds the greatest influence on the firm performance as compared to the other elements (path coefficient = 0.189, p-value = 0.000), and this helps highlight the importance of SCM innovation in improving the firm performance.

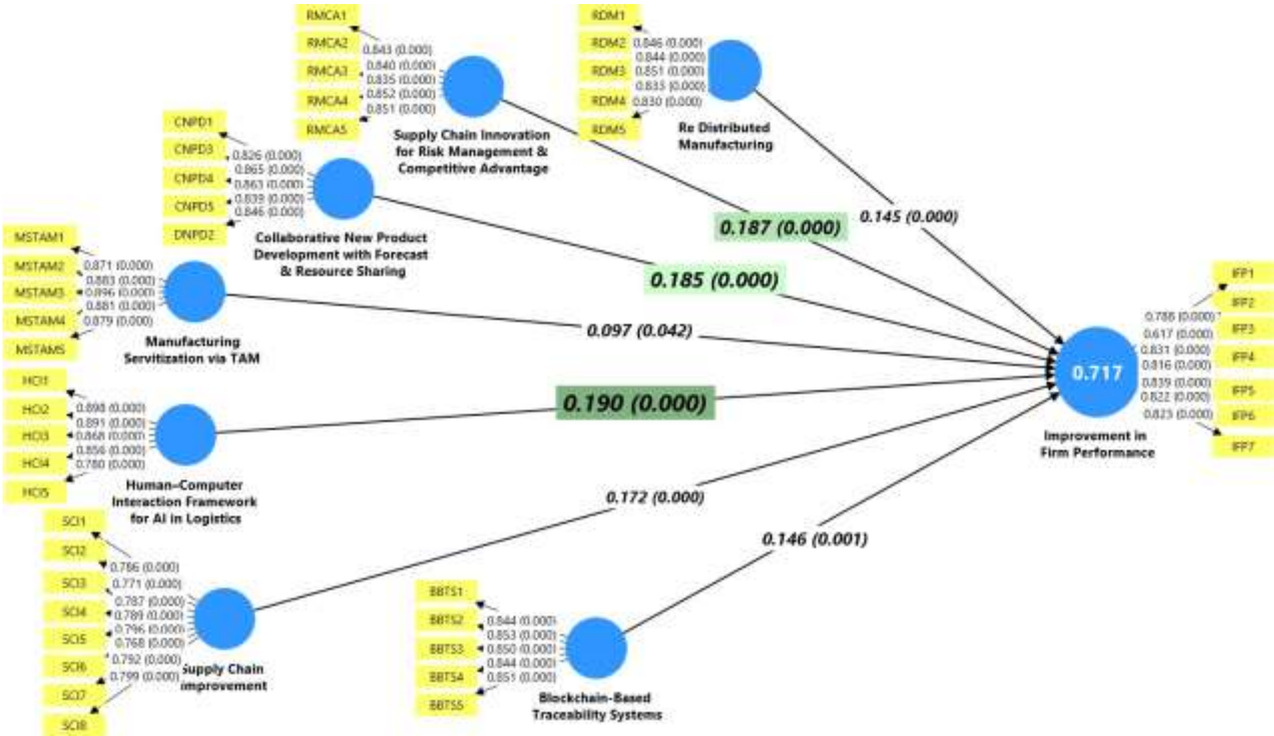

Figure. 2. Structural model representing the significant relationships.

Table 5: Results of hypothesis testing using SEM analysis

Endogenous construct	Exogenous construct	Path Coefficient	Standard error	T statistics	P values	R square	Remark
Improvement in firm performance	Blockchain-based traceability systems	0.147	0.044	3.303**	0.001		Supported
Improvement in firm performance	Collaborative new product development with forecast & resource sharing	0.183	0.044	4.188**	0.000	0.717 %	Supported
Improvement in firm performance	Human–computer interaction framework for AI in logistics	0.189	0.053	3.606**	0.000		Supported
Improveme	Manufacturing	0.095	0.048	2.038**	0.042		Supported

nt in firm performance	servitization via TAM						
Improvement in firm performance	Re-distributed manufacturing	0.145	0.040	3.573**	0.000		Supported
Improvement in firm performance	Supply chain improvement	0.174	0.045	3.865**	0.000		Supported
Improvement in firm performance	Supply chain innovation for risk management & competitive advantage	0.187	0.032	5.87**	0.000		Supported

The findings found in the table illustrates the impacts of various technological innovations that were incorporated in SCM on how firms performance was enhanced. The traceability systems built on block chains revealed a positive and statistically significant impact ($b = 0.147$, $t = 3.303$) on the firm performance, thereby implying that transparency and traceability bring performance improvements to the firms. The relationship in collaborative new product development, forecast and resource sharing are stronger ($b = 0.183$, $t = 4.188$) which means that collaboration and joint use of resources are very helpful in improving the level of innovation and efficiency of the firm. Likewise, the human computer interaction model between AI and logistics ($b = 0.189$, $t = 3.606$) implies that the combination of AI and efficient decision-support systems in the logistics enhances the operational flexibility and outcome of operation of the manufacturing companies. The manufacturing servitization with the TAM that is also with the lowest yet significant effect ($b = 0.095$, $t = 2.038$), that is, service-adding does not do it at a magnitude as large. Re-distributed manufacturing ($b = 0.145$, $t = 3.573$) is another model that has a positive impact on firm performance because it allows local and resilient production approaches. Besides, the enhancement of SCM ($b = 0.174$, $t = 3.865$) plays a huge role in the efficiency and reliability, which shows the relevance of sound supply chain practices. SCM innovation has the highest predictive value in risk management and competitive advantage ($b = 0.187$, $t = 5.870$) making proactive innovation of supply chain a critical driver towards continuous performance growth. Together, these predictors account about 71.7% ($R2 = 0.717$) of the variance in firm performance, which indicates that the explanatory power of the tested framework is excellent. In general, the results verify that digital technologies, collaborative practices, supply chain innovations, and servitization contribute to the improvement of the performance of firms simultaneously, where supply chain innovation has shown the strongest impact.

Table 6: Q-square estimate

	Q^2predict	**RMSE**	**MAE**

Improvement in firm performance	0.701	0.549	0.433

Table 7: Prediction statistics CVPAT

	PLS loss	IA loss	Average loss difference	t value	p value
Improvement in Firm Performance	1.525	2.711	-1.186	14.657	0.000
Overall	1.525	2.711	-1.186	14.657	0.000

Table 6 demonstrates the cross-validated redundancy of the constructs that identifies the predictive relevance of constructs with the use of the Q-square statistic; denoted as 1 - (SSE/SSO) squared prediction error/square observations. It analyses the predictive power of the model on the endogenous variable firm performance by repeating the observed values by applying the PLS-Predicts algorithms. The Q-squared values include a valuable quantitative measure of the ability of the model to predict a large number of important endogenous constructs. These are the values that are necessary in understanding the predictive ability of the model on the behaviour and outcomes of these constructs. Q square of and above 0.701 implies excellence in prediction relevance of the endogenous constructs i.e. firm performance. Table 6 indicates that the Q-square value of the endogenous constructs i.e Improvement in firm performance is 0.701 that is bigger, meaning that the model is more powerful to predict endogenous constructs. A higher predictive relevance indicates that improvement in firm performance is especially good, and thus the ability to predict the model in a somewhat higher way. The prediction statistics have been presented in Table 7 and display the CVPAT where the structural model is contrasted with the linear regression model. The values that are reported are the difference between the average value of loss (Linear model vs PLS model). The loss difference obtained is a negative and average value which indicates that predictive strength of the structural model is superior compared to that of the linear model. It could therefore be concluded that PLS model was superior to the linear model as far as its predictive accuracy was concerned.

IPMA

Table 8 indicates the process by which IPMA uses the path information to identify the relative importance of latent exogenous constructs in the PLS model. Whereas importance is the total effect that is absolute on the final endogenous variable, performance is the size of the latent variable scores. The x-axis was measured on importance. The absolute importance of the other constructs is lower when compared to the absolute importance of "Human-computer interaction framework for AI in logistics. The Y axis was used to compute the performance. The higher mean latent scores in Human-computer interaction framework for AI in logistics imply that it is a more solid construct, as it possesses more constructive measurement paths.

Table 8: IPMA Analysis

	Importance	LV performance
Blockchain-based traceability systems	0.146	61.226
Collaborative new product development with forecast & resource sharing	0.185	62.997

Human–computer interaction framework for AI in logistics	0.190	61.145
Improvement in firm performance		61.742
Manufacturing servitization via TAM	0.097	53.922
Re-distributed manufacturing	0.145	62.001
Supply chain innovation for risk management & competitive advantage	0.187	59.506
Supply chain improvement	0.172	63.740

5. *Discussion*

The results of this research are strong empirical support that technological inventions in supply chain management play a significant role in the performance of firms in the manufacturing industry. Each of the seven investigated innovations, blockchain-based traceability systems, collaborative new product development with forecast and resource sharing, human-computer interaction (HCI) frameworks of AI in logistics, manufacturing servitization through TAM, re-distributed manufacturing, supply chain improvement, and supply chain innovation to risk management and competitive advantage had a positive and statistically significant impact on firm performance. Taken together, the constructs described 71.7% of the variance in the firm performance which is strong evidence of the strong explanatory capability of the proposed model. IoT and AI will be able to enhance accuracy of demand predictions, production scheduling and management of supply chains, lessen lead times, and be more receptive to market environment variations (Li et al., 2023). Supply chain innovation to manage risks and competitive advantage was found to be one of the strongest predictors and supports the thesis statement that supply chain resilience is one of the pillars of performance in uncertain environments. According to the current research, innovation as blockchain, digital twins, and AI-driven analytics increase the visibility of risks and forecasting, enabling companies to predict disruptions and stay on course (Choi and Guo, 2022).
In a similar manner, the human-computer interaction model of AI in logistics became a crucial source of concern, which indicates the value of user trust, explainability, and a smooth integration of human operators and AI systems. Research proves that, in case logistics systems based on AI have adaptive and transparent interfaces, they will not cause resistance to adoption and will enhance operational decision-making (Cai, Luo, and Xu, 2022). The other important finding is that collaborative development of new products through forecast and resource sharing have significant influence on the performance of firms. This highlights the importance of inter-organizational collaboration in speeding up product development, achieving reduced uncertainty and increasing agility of the supply chain. According to recent research, digital platforms could help to enhance the quality of products and time-to-market with the help of collaborative forecasting and resource pooling, which is supported by digital platforms (Huang and Li, 2023; Xie, Chen, and Wang, 2021).Similarly, traceability systems that run on blockchains were also revealed to improve the performance of the firm by enhancing transparency and trust. In line with previous research, the adoption of blockchain boosts collaboration between the firms, enhances compliance, and guarantees the traceability that subsequently minimizes fraud and increases consumer confidence (Queiroz and Fosso Wamba, 2022; Bag, Gupta, and Kumar, 2022). The implications of the results also show that re-distributed manufacturing and manufacturing servitization through TAM have positive effects on firm performance, but with smaller effects than other innovations. These results indicate that although local and service-based supply chains models offer strategic flexibility and

sustainability advantages, they are yet to be felt. As literature indicates, additive manufacturing produces distributed production ultimately leads to reduced reliance on the central supply chains and a sense of resilience (Srai et al., 2021; Khajavi et al., 2022).

In the same vein, servitization under the support of digital technologies helps to improve the relationships with customers and long-term competitiveness, yet its effective implementation requires overcoming the organizational resistance and ensuring the perceived usefulness of the new systems (Baines and Lightfoot, 2023). In general, this research adds to the existing literature on the topic of supply chain digitalization by empirically confirming the beneficial influence of various technological advances on the performance of firms. The findings emphasise the fact that all innovations are value-adding, but the supply chain innovation and AI-based human-computer interaction frameworks have proven the most influential and resilience and competitiveness shaper. Such results have implications to managers and policymakers implying that investments in digital platforms, explainability of AI, and collaborative innovation ecosystems are essential to attain long-term positive influences on performance. Simultaneously, companies also have to overcome obstacles in terms of interoperability, cultural resistance, and governance to gain maximum advantages of such innovations (Kshetri, 2021).

Conclusion

This research offers empirical data that a combination of technological advances in SCM, i.e., blockchain-based traceability, collaborative new-product development and forecasting, human-computer interaction when deploying AI, manufacturing servitization, re-distributed manufacturing, supply-chain improvement practices, and risk-management innovations can significantly boost the performance of firms in the manufacturing sector. The conceptual model under test greatly accounts for a significant share of firm performance, as have the SCM innovation in risk management and HCI-related AI systems. The paper results confirm that the digital transparency, organizational collaboration, and agility in production combination results in greater gains in both operational and financial outcomes in firm performance.

Theoretical Contributions

The research contributes to the current body of SCM literature by introducing several state-of-the-art technological constructs into a forecastive approach, and showing their pronounced impacts, supporting the results of other recent researches in the field of AI and blockchain integration into SCM (e.g., Al-Hourani and Weraikat, 2025). Another perspective that the paper pays attention to is the dynamic capabilities perspective (sensing, seizing, and reconfiguring) and user-level acceptance theories (such as TAM and HCI), where the organizational capability and the individual acceptance are combined in a positive way to influence the performance - which can be further extended by the recent studies on AI-based decision making and human-centric SCM (Samuels et al., 2024; Al-Hourani and Weraikat, 2025). The methodology employed with the combination of technological, organizational and risk-oriented innovation that employs PLS-SEM model offers better predictive power, thereby contributing to practice in empirical research of supply chain and operations management as well as supporting recent systematic reviews that prioritize the use of AI/ML as a tool of resilience and blockchain as a tool of traceability.

Managerial Implications

The paper recommends that to achieve the maximum benefit of supply chain technological investments planned as portfolio and to achieve maximum benefit, firms must focus on AI deployments developed with a robust HCI and user engagement, deploy blockchain to proveance and compliance in high-risk products, and form collaborative forecasting and resource sharing to speed up the development of new products. When applied in support of complementary digital infrastructure, re-distributed manufacturing can be a source of lead-time and sustainability benefits. Though longer term, servitization strategies need to be coupled with training and definite user acceptance strategies. Now since the innovations of supply chain risk management are among the best predictors of performance, managers must also invest in disruption sensing, scenario planning and rapid reconfiguration capabilities. AI/ML is more resilient in its operations (Al-Hourani and Weraikat, 2025), and blockchain offers better traceability, trust and sustainability.

Limitations

There are limited limitations of the study. The research relies on non-probability, judgmental sampling of accumulated survey data of a single nation. The moderating conditions (firm size, partner digital maturity, regulatory environment) that might influence the translation of different technologies into performance are not studied in the study; the interaction effects of moderating conditions should be studied in the future. The study performance measurement is perceptual in nature, a combination of subjective survey information with both objective firm information (e.g., financials, quality, lead-time) or transactional information would further enhance robustness and external validity.

Reference:

1. Al-Hourani, S., & Weraikat, D. (2025). A Systematic Review of Artificial Intelligence (AI) and Machine Learning (ML) in Pharmaceutical Supply Chain (PSC) Resilience: Current Trends and Future Directions. Sustainability, 17(14), 6591. https://doi.org/10.3390/su17146591
2. Bag, S., Gupta, S., & Kumar, S. (2022). Examining the role of blockchain technology in supply chain sustainability. *Technological Forecasting and Social Change, 176*, 121445.
3. Baines, T., & Lightfoot, H. (2023). *Servitization in manufacturing: Pathways towards digital-enabled business models*. Springer.
4. Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120. https://doi.org/10.1177/014920639101700108
5. Cai, Y., Luo, J., & Xu, X. (2022). Human–AI interaction in logistics: Designing for trust and transparency. *International Journal of Production Research, 60*(22), 6881–6896.
6. Casino, F., Kanakaris, V., Dasaklis, T., Moschuris, S., & Rachaniotis, N. P. (2021). Modeling food supply chain traceability based on blockchain technology. *Computers & Industrial Engineering, 152*, 107701.
7. Chen, Y., Li, X., & Yu, W. (2021). Collaborative innovation in supply chains: The role of digital platforms. *Journal of Business Research, 135*, 465–475.
8. Chen, Y., Yu, W., & Li, Z. (2023). Green supply chain technologies and firm performance: The mediating role of sustainability practices. *Sustainable Production and Consumption, 38*, 134–145. https://doi.org/10.1016/j.spc.2023.01.011
9. Choi, T. M., & Guo, S. (2022). Impact of AI and big data analytics on supply chain resilience and firm performance. *Transportation Research Part E: Logistics and Transportation Review, 157*, 102553. https://doi.org/10.1016/j.tre.2021.102553
10. Glikson, E., & Woolley, A. W. (2020). Human trust in AI: Conceptual framework and review of empirical research. *Academy of Management Annals, 14*(2), 627–660.
11. Huang, J., & Li, Y. (2023). Cloud-enabled collaborative product development and supply chain agility. *International Journal of Production Research, 61*(12), 3928–3945.
12. Huang, J., & Li, Y. (2023). IoT-enabled smart manufacturing and supply chain agility: Empirical evidence from China. *International Journal of Production Research, 61*(4), 1123–1140. https://doi.org/10.1080/00207543.2022.2056781
13. Ivanov, D., & Dolgui, A. (2021). OR-methods for coping with the ripple effect in supply chains during COVID-19: Managerial insights and research implications. *International Journal of Production Economics, 232*, 107921.

14. Kamalaldin, A., Linde, L., Sjödin, D., & Parida, V. (2021). Transforming provider–customer relationships in digital servitization: A relational view. *Industrial Marketing Management, 95*, 217–227.
15. Khajavi, S. H., Partanen, J., & Holmström, J. (2022). Additive manufacturing in re-distributed production: A literature review. *International Journal of Production Research, 60*(6), 1893–1914.
16. Kohtamäki, M., Parida, V., Patel, P. C., & Gebauer, H. (2020). The relationship between digitalization and servitization: The role of servitization in capturing the financial potential of digitalization. *Industrial Marketing Management, 89*, 312–327.
17. Kouhizadeh, M., Saberi, S., & Sarkis, J. (2021). Blockchain technology and the sustainable supply chain: Theoretically exploring adoption barriers. *International Journal of Production Economics, 231*, 107831.
18. Kshetri, N. (2021). Blockchain and supply chain management: Opportunities, challenges, and future research. *International Journal of Information Management, 52*, 102064. https://doi.org/10.1016/j.ijinfomgt.2019.102064
19. Li, Y., Tang, Y., & Zhang, Q. (2023). How digital supply chain innovation drives firm performance: Evidence from manufacturing firms. *International Journal of Production Economics, 255*, 108719. https://doi.org/10.1016/j.ijpe.2023.108719
20. Liu, C., Shang, Y., & Wang, J. (2022). Supply chain resilience in the post-COVID-19 era: Insights from manufacturing firms. *International Journal of Logistics Management, 33*(4), 1158–1182.
21. Liu, X., Sun, Z., & Wang, H. (2023). Dynamic capabilities and digital supply chain transformation: Evidence from the manufacturing sector. *Technological Forecasting and Social Change, 191*, 122514. https://doi.org/10.1016/j.techfore.2023.122514
22. Liu, Z., Zhang, R., & Li, T. (2021). Demand forecasting collaboration in supply chains: Effects on performance under uncertainty. *Omega, 101*, 102259.
23. Manupati, V. K., Schoenherr, T., & Ramkumar, M. (2020). Blockchain in manufacturing supply chains: The impact on trust and collaboration. *Computers & Industrial Engineering, 148*, 106679.
24. Queiroz, M. M., & Fosso Wamba, S. (2019). Blockchain adoption challenges in supply chain: An empirical investigation. *International Journal of Information Management, 46*, 70–82.
25. Queiroz, M. M., & Fosso Wamba, S. (2022). Blockchain adoption in supply chain and its impact on firm performance: A resource-based view. *International Journal of Production Economics, 247*, 108400. https://doi.org/10.1016/j.ijpe.2022.108400
26. Queiroz, M. M., Ivanov, D., Dolgui, A., & Wamba, S. F. (2022). Impacts of epidemic outbreaks on supply chains: Mapping a research agenda amid the COVID-19 pandemic through a structured literature review. *Annals of Operations Research, 319*(1), 115–142.
27. Raddats, C., Kowalkowski, C., & Kindström, D. (2023). Servitization and supply chain integration: Implications for resilience and performance. *International Journal of Operations & Production Management, 43*(2), 325–349.
28. Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.
29. Saberi, S., Kouhizadeh, M., Sarkis, J., & Shen, L. (2019). Blockchain technology and its relationships to sustainable supply chain management. *International Journal of Production Research, 57*(7), 2117–2135.
30. Srai, J. S., & Harrington, T. S. (2021). Localised supply systems: Redefining supply chain resilience. *International Journal of Operations & Production Management, 41*(7), 961–986.
31. Srai, J. S., Kumar, M., Graham, G., Phillips, W., Tooze, J., Ford, S., Beecher, P., Raj, B., Gregory, M., Tiwari, M. K., & Ravi, B. (2022). Distributed manufacturing: A new form of sustainable industrialization. *International Journal of Production Research, 60*(18), 5461–5476.
32. Sun, L., Li, X., & Zhang, H. (2022). Adaptive human–computer interaction for AI-based logistics decision support systems. *Decision Support Systems, 159*, 113819.

33. Sun, P., & Liu, H. (2022). Resource sharing and co-creation in supply chain networks: Implications for innovation. *Industrial Marketing Management, 103*, 80–92.
34. Sun, Z., & Liu, H. (2022). The role of IoT and digitalization in building resilient supply chains. *Journal of Manufacturing Technology Management, 33*(6), 921–939. https://doi.org/10.1108/JMTM-08-2021-0317
35. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal, 28*(13), 1319–1350. https://doi.org/10.1002/smj.640
36. Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.
37. Treiblmaier, H. (2019). Toward more rigorous blockchain research: Recommendations for writing blockchain case studies. *Frontiers in Blockchain, 2*(3), 1–15.
38. Tseng, M. L., Islam, M. S., Karia, N., Fauzi, F. A., & Afrin, S. (2022). A literature review on green supply chain management: Trends and future challenges. *Resources, Conservation & Recycling, 176*, 105959.
39. Wamba, S. F., Dubey, R., & Gunasekaran, A. (2021). The performance effects of big data and artificial intelligence in logistics: The mediating role of human–computer interaction. *International Journal of Logistics Management, 32*(2), 377–399.
40. Wang, X., Zhao, L., & Huang, G. (2022). Blockchain-enabled collaborative product development in supply chains: A framework and empirical evidence. *Computers & Industrial Engineering, 168*, 108071.
41. Wang, Y., Han, J. H., & Beynon-Davies, P. (2022). Understanding blockchain adoption in supply chains: A multiple case study approach. *International Journal of Production Research, 60*(19), 5827–5846.
42. Wang, Y., Xu, D., & Zhang, H. (2022). Digital twins in manufacturing supply chains: Applications, challenges, and opportunities. *Computers & Industrial Engineering, 169*, 108276. https://doi.org/10.1016/j.cie.2022.108276
43. Xie, Y., Chen, J., & Wang, Q. (2021). Early supplier involvement in new product development and its impact on supply chain performance. *Supply Chain Management: An International Journal, 26*(5), 573–587.
44. Xu, D., Xu, X., & Li, L. (2022). Cloud-based manufacturing and supply chain performance: Evidence from manufacturing firms. *Computers & Industrial Engineering, 168*, 108082.
45. Zhang, M., & Yu, Z. (2020). Collaborative product development in manufacturing supply chains: A review and future research directions. *International Journal of Production Economics, 227*, 107663.
46. Zhang, X., Tang, Y., & Yu, H. (2023). Digitalization, supply chain integration, and performance: Evidence from manufacturing firms. *Industrial Management & Data Systems, 123*(5), 1214–1236. https://doi.org/10.1108/IMDS-06-2022-0391