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Exploring the role of artificial intelligence in managing agricultural supply chain risk to counter the impacts of the COVID-19 pandemic

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Abstract

Purpose – In India, artificial intelligence (AI) application in supply chain management (SCM) is still in a stage of infancy. Therefore, this article aims to study the factors affecting artificial intelligence adoption and validate AI's influence on supply chain risk mitigation (SCRM).

Design/methodology/approach – This study explores the effect of factors based on the technology, organization and environment (TOE) framework and three other factors, including supply chain integration (SCI), information sharing (IS) and process factors (PF) on AI adoption. Data for the survey were collected from 297 respondents from Indian agro-industries, and structural equation modeling (SEM) was used for testing the proposed hypotheses.

Findings – This study's findings show that process factors, information sharing, and supply chain integration (SCI) play an essential role in influencing AI adoption, and AI positively influences SCRM. The technological, organizational and environmental factors have a nonsignificant negative relation with artificial intelligence.

Originality/value – This study provides an insight to researchers, academicians, policymakers, innovative project handlers, technology service providers, and managers to better understand the role of AI adoption and the importance of AI in mitigating supply chain risks caused by disruptions like the COVID-19 pandemic.

Keywords Artificial intelligence, Structural equation modeling, Supply chain risk mitigation, Agriculture supply chain (ASC)

Paper type Research paper

1. Introduction

The supply chain (SC) is the very foundation of the economy and society, given that it strongly integrates the surrounding environment. The SC ecosystem interactions are complex and prompted by feedback and interrelations among SC, environment, society, and economy. SC's current status results from various transformations, which started from lean and agile to resilient and sustainable SC, reaching the current state of digitalized and viable SC (Ivanov, 2020b). However, in 2020, the lean, agile, resilient, and sustainable (LARS) SC has been sorely tested by COVID-19 global pandemic disruptions. The COVID-19 outbreak raised

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the need for a complete novel decision-making system for SC practitioners (Chesbrough, 2020; Ivanov, 2020a, b). COVID-19 led to potential negative impacts on the world supply chain, with the global economy facing a negative supply shock, which resulted in the shutting down of various factories and subsequent disruption of SC's global network (Chowdhury *et al.*, 2020). Therefore, the SCM's response to such disruptions should impart digital readiness and integrity to the worldwide supply chain. The firms need to redesign and make SC adaptable for the upcoming trade challenges. In the long term, firms need to develop and implement capabilities and action plans related to data sharing and digital readiness for SCs (Betti and Ni, 2020; Doherty and Botwright, 2020). Digitalization can expand the efficiency of the response to the COVID-19 outbreak by enhancing SC flexibility in such situations (Ivanov *et al.*, 2019). Pandemics like the COVID-19 cause-specific SC risks of long duration, high uncertainty, and ripple effect propagation (Ivanov, 2020b). They can also threaten SC's resilience and robustness, as various authors have reported (Ivanov, 2020a, b; Ivanov and Dolgui, 2020). The disruptions caused by COVID-19 have hugely influenced the world economy and weakened various businesses. COVID-19 has also caused instability in the local and global SC (Ivanov, 2020b).

In the same way as the other industries of the global economy, the food industry was also hit hard in terms of huge losses by the pandemic in 2020 (Dash *et al.*, 2021; Chowdhury *et al.*, 2020). The pandemic has badly impacted the agriculture SC regarding risks related to humanitarian problems and uncertain business scenarios, which influenced the world socio-economically. COVID-19 has negatively impacted all four aspects of food security: stability, availability, accessibility, and utilization (Laborde *et al.*, 2020). World food security is questioned due to disrupted "processing, production, and marketing upstream," resulting in risks to fulfilling downstream demand. The unfulfilled demand resulted in supply disruptions, fluctuating prices, and panic buying. The sudden closure of government schemes related to food has put people's nutritional requirements at risk, depending on these schemes. The closure of market, labor shortage and closing of national or international borders have led to food wastage, increase in SC cost, change in consumer behavior, supply and demand disruption, shortage of storage space, loss of income to producers and societal distress due to untimely harvesting, procuring and lack of market availability (Kumar *et al.*, 2021a; McEwan *et al.*, 2020; Goddard, 2020). For example, in a developing country like India, the lockdown was declared on March 25, 2020, further increasing and later removed in various phases (Kumar and Managi, 2020). This lockdown led to disruptions in demand and supply within ASC, increasing the number of infected cases in India (Singh *et al.*, 2020). Producers are facing a loss of income due to labor shortages and more payment for transportation.

Additionally, the sudden closing of markets and lockdown led to demand disruptions. The ASC is under immense stress due to operational risks occurring in a pandemic. These include shortage of labor, cash and raw material, demand and supply uncertainty, insufficient logistics, and lack of information reliability (L'Hermitte *et al.*, 2016). Among the various organizations, the food industry is among the most significant ones, given its role in fulfilling mankind's primary food needs. Firms cannot forecast such incidents, but they should proactively plan to mitigate risks and uncertainties in their value chains caused by such events. These kinds of disruptions require proactive, as well as reactive planning (Yao *et al.*, 2018). The policymakers and managers need to deal with this in real-time as it is still not over (Ker and Cardwell, 2020). Therefore, it is crucial to explore the strategies and technical ways to mitigate the risks caused by COVID-19 on the ASC and analyze digitalization's potential to deal with these disruptions.

Recent technological developments like "cloud computing (CC), internet-of-things (IoT), big data (BD), blockchain (BC), Robotics, and AI" help integrate isolated SC developments into smart and connected Systems of Systems (SoS). These Industry 4.0 technologies will help the agriculture sector become data-driven, agile, intelligent and automated, with end-to-end SC (Lezoche *et al.*, 2020). Until now, AI has received comparatively less attention in SC risk management, in general. However, there has a been a recent spike in AI research due to the availability of advanced computing techniques, machine learning (ML) techniques, and colossal data availability. This has resulted in the increased interest of researchers in SC risk management by exploring AI's potential. Various authors in the literature have also emphasized the need to mitigate the risks caused by SC disruptions with empirical studies' help (Ivanov and Dolgui, 2020; Remko, 2020). Some authors have also suggested digital technologies such as AI, IoT, BD, CC and BC as a solution for mitigating SC risk caused by uncertainties and disruptions such as COVID-19 (Araz *et al.*, 2020; Ivanov, 2020b; Baryannis *et al.*, 2019b). AI adoption in SC and operations management is still beginning (Baryannis *et al.*, 2019a; Dhamija and Bag, 2020).

India positioned itself on 3rd after the USA to rank AI implementation (The Economic Times, 2018). Disruptive technologies, e.g. AI, are making massive positive changes across Indian agriculture, for which the increasing number of agritech startups are working to develop and implement AI-based solutions. AI use on a larger scale can improve the mechanization of Indian agriculture, productivity by supporting precision farming, decision-making related to crop management, markets, and prices. Agritech startups in India are trying to incorporate AI-based solutions for solving cases such as soil fertility, predictive analytics, monitoring crop productivity, and increasing SC efficiency (Singh, 2020). AI-service providers have collaborated with the government to develop AI-based solutions to solve ASC problems and increase crop yield by 30%. For example, the Karnataka Agricultural Price Commission (KAPC) under the Government of Karnataka signed a memorandum of understanding (MoU) in October 2017 for creating a digital solution based on AI for developing a multivariate commodity price forecasting model by integrating AI, Cloud-ML, image processing, and other AI-tools and techniques. Another example of an AI application is an AI-based sowing app developed by Microsoft in collaboration with nonprofit and nongovernmental research organizations, International Crops Research Institute for the Semi-arid Tropics (ICRISAT). The app sends messages to farmers related to sowings, such as planting, weather forecasting, weed-management, harvesting and fertilizer application. The app is supported by Microsoft Cortana Intelligence Suite and Power Business Intelligence (Fernandes, 2020)

Small and mid-size enterprises (SMEs) still need to confirm the evidence of AI benefits. Some recent studies have explored the risk mitigation strategies during a pandemic like COVID-19 (Di Vaio *et al.*, 2020; Singh *et al.*, 2020; Sharma *et al.*, 2020). However, no study has investigated AI's role in lessening the risks caused by the COVID-19 pandemic and improving the flexibility, resilience and robustness of ASC. Therefore, the research objectives (ROs) of this study are as follows:

RO1. To recognize the factors affecting AI implementation in ASC.

RO2. To examine the influence of AI implementation on SC risk mitigation.

The paper investigates the impact of identified factors based on the TOE framework and OIPT theory on AI adoption in Indian SMEs. The TOE framework works on innovation adoption principles and provides comprehensive, precise and beneficial insights for the industry about technology adoption factors and barriers (Lai *et al.*, 2018). The study extends the AI adoption framework to mitigate supply chain risks by adding factors based on OIPT like supply chain integration, information sharing and process factors with TOE-based factors. According to OIPT, the information flow plays an important role in an organization for reducing uncertainty (Galbraith, 1973). There are already many risks and challenges in developing countries like India, and COVID-19 has only made these worsened (Kumar *et al.*, 2021a). There is a need to provide solutions and propose strategies to mitigate risks. The usual business ways need to be reconsidered and redesign as the rapidly changing consumers' attitudes and uncertain business environment due to the pandemic. This study will assist managers in making efficient and effective decisions related to investment in technological solutions such as AI adoption for addressing the need of the moment, which can support quick assessment of market needs and risks for accurately predicting market demand and align production. This study's findings guide the agro-industry in implementing AI to mitigate SC risks amid disruptions like the COVID-19 pandemic. Therefore, the research questions (RQs) are as follows:

RQ1. What impact factors have on AI implementation in ASC?

RQ2. Does AI implementation impact SC risk mitigation of ASC?

This paper is systemized into seven sections, starting with the introduction. The second section is about the literature review and theoretical background, and the third section presents the conceptual model and hypotheses development. The fourth section outlines the research methodology. The obtained findings are shown in the fifth section. The sixth section includes the discussion of the results obtained, and the seventh section states the conclusion. Furthermore, the last section reports the implications and future scope of the study.

2. Literature review

2.1 Risk management and ASC

The available literature was searched on the online database of "Web of Science (WoS) and Scopus." The keywords used on the database to find the relevant articles were SEM, AI, supply chain risk and COVID-19, without considering the time limit. The papers were only limited to review and research articles. Nonpeer-reviewed articles, conference articles and articles that were out of our research scope were removed. AI for SC is capable of risk identification (Ye *et al.*, 2015), risk assessment (Shang *et al.*, 2017) and response (Papadopoulos *et al.*, 2017). Baryannis *et al.* (2019b) argued that AI explores different alternatives that can automatically make decision-making. However, the adoption rate of AI for SC risk management is significantly less. Probable reasons are lack of trust by SC partners, lack of identification of appropriate data, lack of skills and resistance to change (Nguyen *et al.*, 2018). The recent literature on AI is limited and has considerable scope for researchers. The current review papers by Di Vaio *et al.* (2020), Lezoche *et al.* (2020), Liu *et al.* (2020) and Nayak *et al.* (2019) discussed the current status of the application of AI and ML in ASC and challenges to its implementation. Di Vaio *et al.* (2020) investigated AI's role in agri-food SC and the role of SC stakeholders in achieving a sustainable business model in the COVID-19 scenario. Lezoche *et al.* (2020) reviewed more than a hundred papers for analyzing the industry 4.0 technologies application in the SC to understand Agri 4.0 in making decisions more effective and solving issues of ASC. Lezoche *et al.* (2020) presented a list of impacts of industry 4.0 technologies on ASC and challenges to their implementation. Liu *et al.* (2020) reviewed the current status of industry 4.0 by focussing on critical applications of these technologies in ASC and recent challenges to their research. Apart from the review paper, few empirical studies on ASC related to risk management or industry 4.0 application were also found from the literature (Kumar *et al.* 2021a, b; Sharma *et al.*, 2020; Singh *et al.*, 2020). Sharma *et al.* (2020) identified and analyzed risks in ASC caused by COVID-19 disruptions by using "Fuzzy Linguistic Quantifier Order Weighted Aggregation (FLQ-OWA)." Kumar *et al.* (2021a) identified and analyzed risk mitigation strategies for perishable food SC amid COVID-19 by using a fuzzy-best worst methodology (F-BWM). Singh *et al.* (2020) proposed a resilient SC model based on simulation in a developing food SC to match the changing demand and assist decision-makers in-vehicle rerouting according to travel restriction areas. Kumar *et al.* (2021b) identified and analyzed barriers for industry 4.0 application for achieving a circular economy in ASC by using ISM-ANP.

2.2 Role of artificial intelligence (AI) in ASC

AI is considered an innovative technology that can assist the agri-business in facing the COVID-19 pandemic (Di Vaio *et al.*, 2020). Deep learning, physical robots, computer vision, machine learning, experience systems and software robots are the leading AI techniques enhancing product quality and services. The robots help in effective and efficient farming with minimal resource utilization by calculating the exact condition of the soil, water, crop, humidity, temperature and livestock (Di Vaio *et al.*, 2020). The significance of AI in the agro-industry is accelerating because of its ability to reduce food wastage and training costs, support efficiency improvement, improve problem-solving performance, reduce human error, promote creative activities by reducing human intervention, improve sanitation and hygiene of manufacturing sites, and speed up cleaning processing equipment types (Barth *et al.*, 2017; Lezoche *et al.*, 2020). AI automated systems can collect massive data on a single food and quickly analyze it (Barth *et al.*, 2017). AI techniques can contribute to service creation, identification of knowledge models and decision-making to promote various agri-food applications (Coulibaly *et al.*, 2019). AI provides conventional standard algorithms to accurately evaluate performance and predict patterns that can solve knowledge and production planning issues in ASC (Lezoche *et al.*, 2020).

2.3 Research gaps

From the available literature on SC risk management, we have seen that authors have explored risk management strategies to mitigate the risks caused by uncertainty and disruptions in ASC (Kumar *et al.*, 2021a; Sharma *et al.*, 2020; Singh *et al.*, 2020). Apart from risk management strategies, the impact of disruptive technology on risk mitigation performance needs to be validated for increasing AI adoption in ASC to face uncertainties like COVID-19, as suggested by Di Vaio *et al.* (2020). But, for motivating AI adoption in SC first, there is a need to address the research gap of no study on factors impacting AI adoption in the uncertain environment to mitigate risks. In previous literature, authors have explored the effect of entrepreneurial orientation (Dubey *et al.*, 2020) and institutional pressure on resources. Then the impact of resources (Bag *et al.*, 2020) on the big data analytics-powered AI through SEM. The authors have explored the role of various factors, including SC strategies and culture, on SC risk management performance and SC resilience by using partial least squares of SEM (PLS-SEM) (Mandal, 2020; Can Saglam *et al.*, 2020). Some have explored SC resilience, technology providers' resilience, co-operative resilience and the moderating role of technology orientation using SEM (Çankaya, 2020; Mandal, 2017; Subramanian and Abdulrahman, 2017). Di Vaio *et al.* (2020) discussed AI applications in ASC, especially in the condition of sustainability and the COVID-19 pandemic. However, some authors have explored technology's conceptual role, such as Industry 4.0, AI and digitalization, in risk management (Ivanov and Dolgui, 2020; Baryannis *et al.*, 2019b). But, only a few authors (Subramanian and Abdulrahman, 2017 for CC service providers) have empirically considered technology in their risk assessment and SC resilience studies. Also, no author has discussed the role of AI for managing risk in the SC, statistically.

3. Conceptual model and hypothesis development

This study on artificial intelligence and supply chain risk mitigation has proposed a model based on the TOE framework (Tornatzky *et al.*, 1990) and OIPT (Galbraith, 1973). Some authors have also previously used the TOE framework (Wong *et al.*, 2020; Lai *et al.*, 2018) and

OIPT theory (Srinivasan and Swink, 2018; Fan *et al.*, 2016, 2017) to construct their techno-managerial model.

For analyzing the impact on technology adoption decision, the TOE framework is used as it provides a more holistic view of the technology adoption (Mohtaramzadeh *et al.*, 2018), and it also combines both human and nonhuman factors, which is the reason for its dominance over other IT adoption models (Awa *et al.*, 2017). The technological factors include features and availability of technology. The organizational factors include the firm's resources, infrastructure and internal communication. Environmental factors include SC risks caused by disruption to the market and the external industrial environment.

The other three factors: process factors, information sharing and SC integration, are based on OIPT theory. For mitigating risks caused by disruption, firms need to organize and utilize information efficiently in executing AI adoption, which involves uncertainty (Galbraith, 1973). According to OIPT, information is the most critical flow in organizations, which reduces uncertainty. The linkage between information and its management or use is the most significant performance indicator. The selection of factors is based on "managing the environment and creating self-contained tasks" from OIPT. OIPT is used because it is a comprehensive approach for SC risk mitigation (Fan *et al.*, 2017). The primary function is to produce the most suitable configuration of firm units to support the effective collection, processing and sharing of information (Daft *et al.*, 1987; Galbraith, 1973; Tushman and Nadler, 1978). Our proposed model for AI adoption to mitigate risks, SC integration and information sharing presents the firm's information processing capabilities, and the process factor denotes information processing needs. These three factors are designed for viewing the impact of SC disruption on a firm's needs, capabilities and business environment.

The Delphi study (Skulmoski *et al.*, 2007) was conducted for these eight factors extracted from the literature by giving the preliminary questionnaire to seven experts, and qualitative responses were collected. The Delphi expert panel approved the list of all factors. After this, a pilot study was conducted in 9 firms to confirm the group of factors found from the Delphi study. A 7-point Likert scale was used to collect 108 responses. The pilot study reduced the items list of factors from 56 to 42. Table 2 provides the list of items of factors. Our study focuses on factors that impact technology adoption and another impact of AI on supply chain risk mitigation. The proposed model includes six factors that have a probability of affecting AI. The measurable variable SCRM indicates the AI-embedded ASC risk performance. The proposed conceptual model and its factors are shown in Figure 1.

3.1 Technology factors (TF)

The technology factor has been used by Wong *et al.* (2020) for the BC adoption model in SCM. Data quality is a crucial factor in the successful execution of Industry 4.0 (Luthra and Mangla, 2018). In AI applications, several electronic machines and technology platforms, namely, big data, IoT, cyber-physical system (CPS), etc., are interconnected. The low quality in terms of unauthentic and purposeless data can impact real-time decision-making. The supply chain network is complex and includes various types of players that differ in geography, culture and financial terms that limit technology availability. Due to fewer financial and technical sources and poor connectivity of the Internet and electricity, real-time information management through AI-based drones and robots may be problematic (experts' opinion). The workers and professionals need to know each stakeholder's necessary activities, interdependencies and roles in the highly complex ASC structure. SC professionals lack the competency to manage data storage complexity, analysis and interpretation for significant Industry 4.0 implementation (Luthra and Mangla, 2018). Availability of universal standardization and regulations for data security and privacy, data utilization and analysis, technology handling and information sharing for the AI-based information

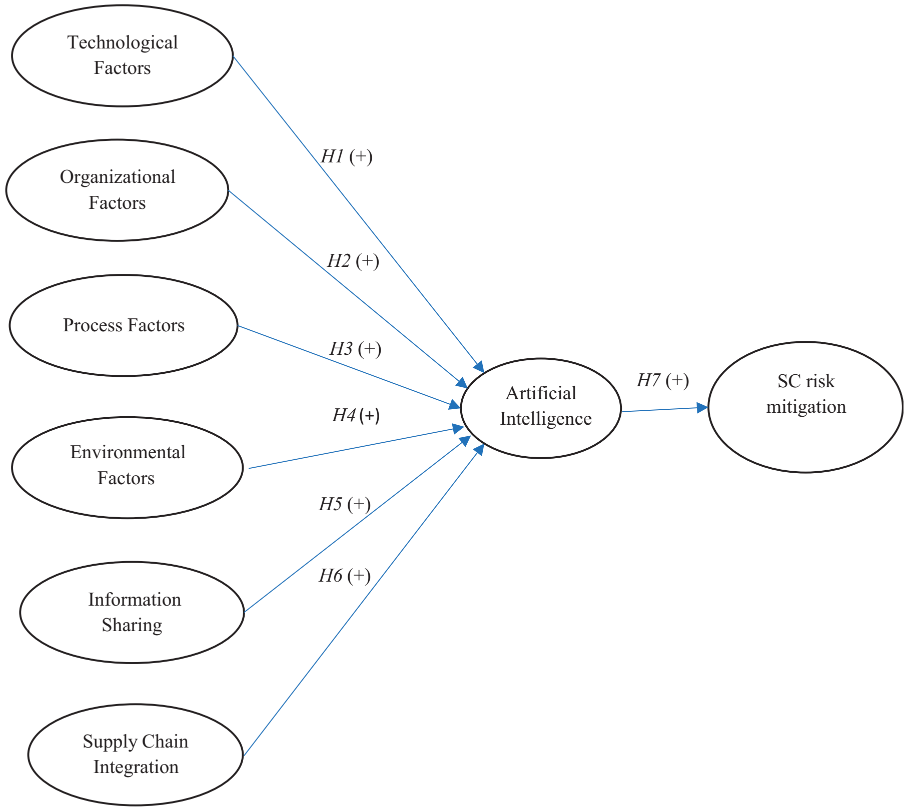

Figure 1.
Conceptual model

system plays an essential role in AI adoption (Serazetdinova *et al.*, 2019). AI technology needs further developments on visualization, adaptability, recognition for nonavailability of the answer, and sensor technology advancement for data collection and data processing through ML for on-time information management (Lezoche *et al.*, 2020). Lack of knowledge and awareness about AI technology can lead to low trust in technology and low acceptance by managers and consumers (Astill *et al.*, 2019).

H1. The technology factor is positively influencing artificial intelligence.

3.2 Organizational factors (OF)

In this study, organizational factors have been taken as one of the TOE model factors as studied by Wong *et al.* (2020) for behavioral intention for adopting blockchain in the SC of SMEs. Management of a firm takes the final decision related to finance, resources and new product development. Investing in the upgradation of technology also needs to be reviewed before the final decision of any technology implementation. For decreasing the overall cost of service and product, there is a need to evaluate hardware and facility costs, operations and maintenance costs, etc. (Wong *et al.*, 2020). The supply chains may have internal organizational barriers in terms of low innovation capability, lack of required infrastructure, technical expertise and experience, which may resist the smooth implementation of AI. For the success of any new project, teamwork and the proper functioning of available infrastructure, including machine, equipment, hardware and software, play an essential role in avoiding the breakdown of information technology and related information (Garvey *et al.*, 2015; Ojha *et al.*, 2018).

H2. The organizational factor is positively influencing artificial intelligence.

3.3 Process factors (PF)

The process factor variable has been newly introduced for this type of structural modeling study with expert opinion to fit in COVID-19 like scenario. The SC faces problems in connecting players electronically to communicate and design an adaptable interface. CPS network requires integrating various heterogeneous components to support effective communication and data analysis (expert opinion; Luthra and Mangla, 2018). Inventory management and control were taken as one of the supply chain strategic capabilities to mitigate inventory-related risks by Vishnu *et al.* (2019). Inventory damage and inventory shortage are the potential risks in supply chain management (Garvey *et al.*, 2015). Responding effectively and quickly to the change in product design and customization requirements is one of the supply chain agile strategies (Çankaya, 2020). The product's quality issues from the supplier and manufacturer side are the risk factors used by Ojha *et al.* (2018). Lack of laborers due to the pandemic situation led to increasing employee workload and disruption in the SC due to the sudden closing of manufacturing plants and transportation modes to prevent the infection (Ivanov, 2020b; Ojha *et al.*, 2018; Garvey *et al.*, 2015; Betti and Ni, 2020).

H3. The process factor is positively influencing artificial intelligence.

3.4 Environment factors (EF)

The environmental factors have been used by Wong *et al.* (2020) in their conceptual model, with several subfactors *viz.*, market dynamics, regulatory support and competitive pressure. In the case of disruptions in the SC, an emergency service is introduced that increases transportation costs. Transportation modes to transfer products from distribution centers (DCs) to the customer, equipped with advanced communication technology and infrastructure, need risk mitigation caused by disruptions (Azad *et al.*, 2014; Gravili *et al.*, 2018). Transportation of products may face heavy traffic conditions due to poor infrastructure of transportation modes. This leads to disruption of suppliers and negatively affects the delivery of raw material to the production plant and the final product to the customer (Ojha *et al.*, 2018). Variations in supply and demand and the subsequent price volatility and market dynamics, combined with disruptions caused by accidents or natural adversities, can lead to cost, time and resource loss led by inefficient predictability and flexibility performance (Garvey *et al.*, 2015; Blos *et al.*, 2018).

H4. The environmental factors are positively influencing artificial intelligence.

3.5 Information sharing (IS)

Information sharing (IS) is the foundation of the current business environment; significant IS plays an essential role in the efficient operational functioning of agriculture SC as ASC is complex, competitive and dynamic (Li *et al.*, 2005). IS improves collaboration and increases partnerships among SC players (Kim and Chai, 2017). Sharing information related to the production schedule and the cost with suppliers improves supplier development, the relationship between supplier and industry, and promotes new product development (Çankaya, 2020). Through efficient and quality information sharing, effective knowledge sharing can be gained to help SC become agile and dynamically capable while becoming transparent (Narwane *et al.*, 2020). Information quality affects performance more of some attributes of food products, and information sharing benefits for some characteristics appear only at a high cost (Zhang *et al.*, 2020). Inefficient and limited information sharing technologies and systems lead to information breakdown (Ojha *et al.*, 2018) and can hinder the efficiency of multitier SCRM (Wang-Mlynek and Foerstl, 2020).

H5. Information sharing is positively influencing artificial intelligence.

3.6 Supply chain integration (SCI)

The SCI factor is incomplete without integrating the firm within and among the SC stakeholders. Integrating the supply chain is a strategic aim of business management that can be easily pursued with Industry 4.0 applications. The performance factors like new product flexibility, sales, market growth, customer satisfaction, manufacturing cost, increased delivery flexibility, improved lead time, improved product quality and sustainable performance are positively related to supply chain integration. SCI is only possible when all SC players share a common database, managerial and technical skills, software and technological infrastructure or platform (Chiarini *et al.*, 2020). Internal integration here refers to the communication, information and knowledge sharing between the departments (Çankaya, 2020; Liu and Lee, 2018). The total cost that includes manufacturing, production, dispatching and transportation needs to be calculated in the situation of disruption for assessing the SC risk propagation (Ojha *et al.*, 2018).

H6. Supply chain integration is positively influencing artificial intelligence.

3.7 Artificial intelligence (AI)

SC risk management includes collaborative efforts of all players involved in mitigating risks for decreasing vulnerability and increasing SC's robustness and resilience to ensure profitability (Baryannis *et al.*, 2019b; Liu *et al.*, 2019). Flexibility level incorporation in SC risk management is helpful in meeting the targets of SC risk mitigation. Flexible SC is obtained using fuzzy programming methods under AI techniques (Baryannis *et al.*, 2019b). The novel technologies, namely, Big data, IoT, BC, CPS and AI, significantly reduce the uncertainty by collecting real-time data and ensure its analysis with the help of intelligent and automated decision making, which will enhance the flexibility, efficiency and resilience of the end to end ASC (Lezoche *et al.*, 2020). The dynamic nature of SC risk management decision-making induces the application of AI-based modeling and simulation techniques to mitigate risks in SC (Baryannis *et al.*, 2019b). AI combines voluminous expert intelligence and helps reduce human errors up to some level to reassess transactions that human experts can omit. The expert system in AI improves decision-making, promotes on-time, low-cost, expert-based decisions and improves the available data (Lezoche *et al.*, 2020).

H7. Artificial Intelligence is positively influencing SCRM.

3.8 Supply chain risk mitigation (SCRM)

This study includes SCRM practices to develop an effective risk management plan and evaluate SC's risk mitigation performance. These practices target minimizing the adverse impacts of risks (Chang *et al.*, 2015). A firm's SC can adjust the supplier's delivery time and delivery schedule to mitigate SC disruptions and avoid delivery risks by making on-time delivery of the products (Can Saglam *et al.*, 2020). SC risk analysis can be improved with the effective monitoring and tracking of product activity or flow (Baryannis *et al.*, 2019b). Effective monitoring of product flow along the SC or improved traceability will also enhance the product quality and update products' availability. Product quality and availability are critical risks that need to be evaluated and mitigated in the COVID-19 era (Ojha *et al.*, 2018;

Chowdhury *et al.*, 2020). The SC needs to access real-time data to ensure resilience and effective decision-making with proactive planning and improve the recovery plan's performance (Kara *et al.*, 2020). For mitigating the risk, machines and equipment need adequate maintenance to increase their reliability (Hosseini *et al.*, 2019).

4. Research methodology

4.1 Survey design and pilot study

The survey items were drafted from the available literature on SCRM and technology adoption. The prepared questionnaire was pretested in depth by three senior managers from three different firms and four academicians in the relevant area to collect opinions about its suitability. A Likert scale with 07 (seven) points was used to collect the response to the questionnaire. The pretest resulted in the reframing of the questionnaire following the feedbacks of the experts. After reformulating the survey, a pilot test was conducted through a telephonic interview with ninety-nine firms found on the Centre for Monitoring Indian Economic (CMIE). The survey was again altered in line with the suggestions of firms. The final survey for the collection of data on the field was prepared. The survey was designed into three sections but not evenly distributed in terms of question numbers. The first section was designed for SC managers and senior managers. The second targeted information technology (IT) managers and the third was directed to innovative project handlers.

4.2 Data collection and population

The study was focused on Indian firms engaged in SC activities such as procurement, manufacturing and production, distribution, transportation and customs clearance. Overall, five hundred and fifty-four (554) firms with more than or equal to 50 employees drawn from the CMIE database were contacted for the survey. Out of 554 firms, 451 responded, but only 297 response forms were helpful for the final analysis. Responses were collected through telephonic interviews of the IT managers, innovative project handlers, SC managers and senior managers by five trained interviewers. These interviewers were also supervised and instructed by the researchers to ensure smooth and unbiased data collection. The interview was organized from August 28, 2020, to October 15, 2020, by spending 4–5 h daily with the interviewers. An online survey was also framed for the respondents who disagreed with interviewing during regular working hours and were not interested in response collection interviews. If any one of the sections remained unanswered, then the respondents were contacted again by the interviewers.

The demographic profile of the 297 respondents is presented in Table 1, which is similar to the agri-food industrial sector. Most of the respondents of the survey were from the dairy sector (31.31%), followed by the beverage industry (25.58%) and bakery and confectionery (24.91%).

4.3 Common method bias (CMB) and nonresponse bias (NRB)

In this study, respondents were kept anonymous, independent to respond to the questionnaire's questions as per their convenience, and responses were collected only from the qualified ones. These steps, including pretest and involving three respondents in a relevant area (SC management, IT, and innovative project handlers), helped lower the standard method bias potential (Podsakoff *et al.*, 2003). Harman's one-factor test was performed to look up the CMB (Podsakoff and Organ, 1986). Harman's one-factor test, with eight first-order factor inputs, displayed that the first factor described only 14.863% of the variance (as mentioned in supplementary material). The remaining variance was dispersed equally among the other factors.

Items		N (297)	%Age
Industry type	Beverage	76	25.58
	Dairy	93	31.31
	3PL	12	4.04
	Spices and condiments	42	14.14
	Bakery and Confectionary	74	24.91
Total		297	100%
Firm size	>50	118	39.73
	>150	179	60.26
Total		297	100%
Designation of respondents	SC manager	134	45.11
	SC senior manager	52	17.5
	IT manager	80	26.93
	Innovative project handlers	31	10.43
Total		297	100%
Age	25–35	130	43.77
	36–55	110	37.03
	56–75	57	19.19
Total		297	100%
Gender	Male	152	51.17
	Female	145	48.82
Total		297	100%
Educational qualification	UG	90	30.30
	PG	148	49.83
	PhD	59	19.865
Total		297	100%
Years of experience	0–5	75	25.25
	5–10	63	21.21
	10–15	81	27.27
	15–20	78	26.26
Total		297	100%

Table 1.
Sample population ("demographic profile")

All the valid 297 responses obtained via interview or e-mail medium were divided into two groups: early response with 189 responses in the 1st group and late response with 108 responses in the second group. For testing the NRB, a *t*-test was carried out to compare the two groups (Armstrong and Overton, 1977). No proof of statistically significant difference ($\alpha = 0.05$) was obtained between the two groups of timely and delayed responses as the *p*-values ranged between 0.010 and 0.990 (as shown in Annexure). This proves that NRB does not exist in the population.

4.4 Factor analysis and structural equation model

Factor analysis (FA) methodology is used to affirm the dimensionality of scale. There are two types of FA: "Confirmatory factor analysis (CFA) and Exploratory factor analysis (EFA)." EFA facilitates the identification of the measurement model and the interrelationships between the model variables. EFA also investigates the nature and pattern of the model variable to construct a more transparent model and reduce the number of constructs from the broad set of underlying constructs. On the other hand, CFA facilitates evaluating the final measurement model for validation and more refining. (Ahire *et al.*, 1996). SEM is used to determine the latent construct's measurement with the help of indicators and to evaluate the effects between the factors (Hair *et al.*, 2009). It is an effective statistical tool to analyze interrelationships between dependent and independent factors by utilizing statistical data and qualitative assumptions.

Construct	Measurement items	Items	Loading	α	Authors
Technology factors (TF)	Data quality	TF1	0.938	0.961	Wong *et al.* (2020), Lezoche *et al.* (2020), Serazetdinova *et al.* (2019), Serazetdinova *et al.* (2019), Astill *et al.* (2019), Luthra and Mangla (2018)
	Technology availability	TF2	0.928		
	Network complexity	TF3	0.918		
	Standards for technology application	TF4	0.914		
	Immature technology	TF5	0.850		
	Technology knowledge	TF6	0.834		
Organizational factors (OF)	Financial constraint	OF1	0.614	0.9031	Wong *et al.* (2020), Ojha *et al.* (2018), Garvey *et al.* (2015)
	Internal organizational practices	OF2	0.994		
	Management support	OF3	0.575		
	Equipment breakdown	OF4	0.968		
	Collaboration/ collaborative work	OF5	0.601		
	IT infrastructure breakdown	OF6	0.567		
Process factors (PF)	IT interface problem	PF1	0.913	0.9364	World Economic Forum–WEF (2020), Çankaya (2020), Ivanov (2020a), Vishnu *et al.* (2019), Luthra and Mangla (2018), Ojha *et al.* (2018), Garvey *et al.* (2015), Ojha *et al.* (2018)
	Inventory management	PF2	0.863		
	Decision making	PF3	0.845		
	Quality issues	PF4	0.855		
	Employers skills	PF5	0.845		
Environment factors (EF)	Transportation resource	EF1	0.743	0.8474	Wong *et al.* (2020), Gravili *et al.* (2018), Blos *et al.* (2018), Ojha *et al.* (2018), Garvey *et al.* (2015), Azad *et al.* (2014)
	Complex traffic condition due to flooding	EF2	0.759		
	Delivery delay	EF3	0.717		
	Cost, time and resources loss	EF4	0.720		
	Accidents	EF5	0.689		
Information sharing (IS)	Improves information quality	IS1	1.008	0.8497	Kim and Chai (2017), Çankaya (2020), Narwane *et al.* (2020), Zhang *et al.* (2020), Wang-Mlynek and Foerstl (2020), Ojha *et al.* (2018), Li *et al.* (2005)
	Information sharing technology	IS2	0.959		
	Customer information	IS3	0.572		
	Manufacturer information	IS4	0.466		
Supply chain integration (SCI)	Supplier integration	SCI1	0.858	0.8429	Chiarini *et al.* (2020), Çankaya (2020), Liu and Lee (2018), Ojha *et al.* (2018)
	Customer integration	SCI2	0.771		
	Internal integration	SCI3	0.688		
	Information integration	SCI4	0.716		
Artificial intelligence (AI)	Decision making	AI1	0.692	0.7852	Lezoche *et al.* (2020), Baryannis *et al.* (2019b), Liu *et al.* (2019)
	Demand forecasting	AI2	0.649		
	Flexibility	AI3	0.637		
	Resilience and robustness	AI4	0.647		
	Expert system	AI5	0.624		

Table 2.
Measurement items, loading factors, Cronbach's alpha (α)

(*continued*)

Construct	Measurement items	Items	Loading	α	Authors
SC risk mitigation (SCRM)	On-time delivery	SCRM 1	0.930	0.9639	Can Saglam *et al.* (2020), Kara *et al.* (2020), Chowdhury *et al.* (2020), Baryannis *et al.* (2019b), Hosseini *et al.* (2019), Ojha *et al.* (2018), Chang *et al.* (2015)
	Monitor and tracking product activity	SCRM 2	0.919		
	Manufacturing and production cost	SCRM 3	0.907		
	Machine downtime	SCRM 4	0.886		
	Real-time data	SCRM 5	0.881		
	Transportation cost and dispatching cost	SCRM 6	0.854		
	Product quality and availability	SCRM 7	0.853		

Table 2.

In contrast to other regression techniques, SEM helps answer a group of related research questions in a single and organized way by modeling relationships between various constructs concurrently (Gefen *et al.*, 2000; Gerbing and Anderson, 1988). The authors have also used SEM in previous studies (Çankaya, 2020; Mandal, 2017). The SEM in this study will also help understand the causal relationships among dependent and independent variables in the proposed model. The Analysis of Moment Structures (AMOS) 21.0 software is used to create and explore path diagrams. The reliability of the measurement model and the validity of the constructs were also affirmed using Cronbach's alpha and convergent, content and divergent validity.

5. Research findings

5.1 EFA and CFA

After ensuring the content validity using a measurement method from the literature, a construct reassessment was performed with experts from the relevant area and a pilot study on firms. After this, AMOS 21.0 software was used to carry out EFA based on principal component analysis with Varimax Rotation for identifying the structural relationships among the scale items employed. The same method has been utilized in earlier research articles to ensure the final measurement model (Subramanian and Abdulrahman, 2017; Can Saglam *et al.*, 2020; Çankaya, 2020). The "Bartlett's test of sphericity" with significance level 0.000 and the "Kaiser–Meyer–Olkin (KMO) value for the adequacy of sampling (0.877)" assured EFA's data suitability. The reliability of the scale was checked by using Cronbach's alpha values. In the EFA test, "Cronbach's alpha values > or = 0.7" are significant, but 0.6 represents adequate value; however, this does not always mean internal consistency of high degree because the value of alpha is also influenced by the length of the proposed conceptual model or their items per construct (Merschmann and Thonemann, 2011; Muduli *et al.*, 2020). The EFA results confirmed that all the factors had "Cronbach's alpha value more than 0.6," as shown in Table 2. Table 2 shows that "Cronbach's alpha value limits from 0.7852 to 0.9639," indicating that the test instrument is quite reliable (Nunnally, 1978).

After EFA, CFA was executed to confirm the relational model, and the foundation of convergent validity was also laid by using AMOS 21.0. The loadings of all the constructs were found to be more than 0.5. at $p < 0.01$. In our model fit, the fit indices' values are: "Chi-square test value = 1.829"; "root means square residual (RMR) = 0.073"; and "root means a square error of approximation (RMSEA) = 0.053." Thus, the goodness of fit indices was at an allowable level. The factor loadings gained from CFA were more than 0.567 except for IS1, i.e.

0.471. CFA findings can also be utilized for testing convergent validity (CV) (Carr and Kaynak, 2007). The composite reliability (CR) and average variance extracted (AVE) values were calculated to test CV to show each construct's relationship with the other variables. Table 3 shows that AVE is greater than 0.5, and the CR value is also greater than the AVE value. Therefore, the CV of the measurement model is supported.

The discriminant validity (DV) is used to test whether the construct measures that seem unrelated are so. Table 3 denotes that the square root of the AVE of each construct is greater than the correlation of the construct with the other constructs, which proves that DV exists (Fornell and Larcker, 1981).

After the confirmation for scale dimensionality, the final theoretical structural model test for hypotheses testing was performed as presented in Table 4. SEM's main advantage is that it combines both visible and invisible variables (Hair *et al.*, 2017) and tests indirect influence (Bagozzi and Yi, 2012). SEM also allows the testing of all the hypotheses simultaneously (Abdallah and Nabass, 2018). Figure 2 shows the findings of SEM applied by the use of AMOS 21.0. All model fit indices showed satisfactory results at an acceptable level: "Chi-square test value = 1.869; Tucker Lewis. index (TLI) = 0.925; confirmatory fit index (CFI) = 0.929 and RMSEA = 0.054." Table 4, which enlists the hypotheses testing findings, shows that the process factor positively influences artificial intelligence ($\beta = 0.144, p < 0.05$). Information sharing positively influences artificial intelligence ($\beta = 0.096, p < 0.05$). SC integration influences artificial intelligence ($\beta = 0.311, p < 0.05$). Artificial intelligence also positively influences supply chain risk mitigation ($\beta = 0.316, p < 0.05$). The rest of the hypotheses, namely, H1, H2 and H4 were rejected. This indicates that the technological, organizational and environmental factors have a nonsignificant negative relation with artificial intelligence.

The mediation test was also conducted for AI as a mediator between the independent variables and SCRM. The findings of the mediation model test are shown in Table 5. Full mediation was found for SCI and PF, whereas no mediation effect was found for other independent variables. Table 5 provides the detail of regression weight, indirect and direct effects. The mediation model also explains the causal impact of predecessor on dependent variable directly and indirectly (Hair *et al.*, 2011). Full mediation means only indirect effect exists, and no mediation means no indirect effect (Lowry and Gaskin, 2014). The result shows that only SCI and PF; thus, only SCI and PF are focused on the AI adoption model. The remaining independent variables- TF, OF, EF and IS also need to be considered for AI adoption in Indian ASC.

5.2 Qualitative findings

AI in application in ASC is only limited to narrow AI application that is limited to ML techniques for supply and demand planning at processor and logistics service providers end, Chatbots, self-driving machines and sensors for monitoring soil and plant condition and weather forecasting to assist in real-time monitoring of plant condition for its fertilizer and water requirement. AI technology is mainly applied at the farm level in image processing and ML algorithms and for supply planning in ML techniques for forecasting and compromising demand and supply gap by using preprogrammed decisions. But, there is still a gap in linking all SC players under one umbrella called AI-SoS, which combines AI with IoT, BC, BD, CC and CPS, which can be the driver for the effective supply chain management. Combining AI with IoT can be the best solution for making automated decisions in SCM through learning capabilities of AI and providing structured interpretations of the collected unstructured data. Currently, the implementation of AI-SoS is in its developmental stage in Indian ASC, and there is a long way ahead to achieve full automation through AI. AI systems need to collect sufficient and accurate end-to-end

Table 3. Composite reliability (CR), average variance extracted (AVE) and discriminant validity

	CR	AVE	TF	OF	PF	EF	IS	SCI	AI	SCRM
TF	0.9677	0.8333	0.9128							
OF	0.9191	0.6549	0.098	0.8688						
PF	0.9509	0.795	0.283**	0.141*	0.8916					
EF	0.7453	0.8009	0.046	0.084	0.282**	0.894				
IS	0.8993	0.7923	0.148*	0.067	0.152**	0.257**	0.8901			
SCI	0.8947	0.7801	−0.009	0.035	−0.027	−0.026	−0.048	0.8832		
AI	0.8526	0.8365	−0.016	0.112	0.028	0.062	−0.026	0.001	0.914	
SCRM	0.97	0.822	0.035	0.051	0.114	0.388**	0.265**	−0.018	−0.008	0.906

Note(s): "*. Correlation is significant at $p = 0.05$ (2-tailed)"
"**. Correlation is significant at $p = 0.01$ (2-tailed)"

SC data and external environment data for accurate forecasting and automated decision making for which implementation of industry 4.0 is required at all stages of SC. Indian ASC lacks in the mature level of AI implementation due to some constraints such as dependency on weather and its changing conditions, lack of sufficient data due to lack of digitalization, unavailability of data, security and privacy of data, and the gap between farmers, AI-service providers and researchers. Therefore, the saturation level of AI adoption is not achieved in ASC in India; however, it is explored up to some extent at the farm level, price estimation of agricultural commodities and modeling of market variability. There is a wide gap in implementing AI-based technology systems in ASC to face business environment uncertainty created by pandemics like COVID-19 by accurate forecasting with the help of predictive learning.

6. Discussion

This paper aims to analyze the impact of organizational, technological and environmental factors, apart from process factors, supply chain integration and information sharing on artificial intelligence ("H1, H2, H3, H4, H5 and H6") and then the impact of AI on supply chain risk mitigation (H7). This section presents the possible reasons for accepting and rejecting the proposed hypotheses based on literature and survey findings. Table 4 outlines the hypotheses testing results and shows that the SEM analysis of the proposed conceptual model supports four hypotheses, including AI's relation with supply chain risk mitigation. The three hypotheses in order of their standard estimates are H6: Positive relation of supply chain integration with AI; H3: Positive relation of process factor with AI; and H5: Positive relation of information sharing with AI.

The positive relation of artificial intelligence with supply chain risk mitigation is the most significant and supported by the SEM analysis. The artificial intelligence capabilities that include real-time data collection, expert systems, error reduction and ML techniques make it useful for making SC resilient, flexible and robust (Lezoche *et al.*, 2020; Baryannis *et al.*, 2019b; Min, 2010). The real-time data availability and monitoring of products and SC help solve the risks associated with product quality and its availability (Rodríguez-Espíndola *et al.*, 2020; Massaro and Galiano, 2020). With other emergent technologies, AI-enabled automated systems with better decision-making ability for simple to complex tasks have been replacing the workforce in many firms and service industries; this leads to significant cost reduction and increment inefficiency (Dwivedi *et al.*, 2019). AI has a low-cost processing advantage due to CC's invention (Agrawal *et al.*, 2017). An AI technology like Intelligent Chatbots can increase delivery service efficiency by making it on time and reducing the service delivery cost. However, SC's overall cost after AI implementation still needs to be explored more (Dwivedi *et al.*, 2019). Training costs, low-cost expert-level decisions and low-cost agricultural technologies are advantages of AI implementation in ASC (Lezoche *et al.*, 2020). AI implementation benefits reduce overall cost, equipment cost and production cost

Table 4.
Path, coefficients, standard deviation and *p*-values

Hypotheses	Path	Coefficients	Standard deviation	*p*-values	Decision
H1	TF → AI	−0.011	0.0114	0.859	No
H2	OF → AI	−0.055	0.0247	0.379	No
H3	PF → AI	0.144	0.1207	0.027	Yes
H4	EF → AI	−0.034	−0.0293	0.610	No
H5	IS → AI	0.096	0.1095	0.0120	Yes
H6	SCI → AI	0.311	0.2339	***	Yes
H7	AI → SCRM	0.316	0.3108	***	Yes

Note(s): *** Correlation is significant at the 0.05 level

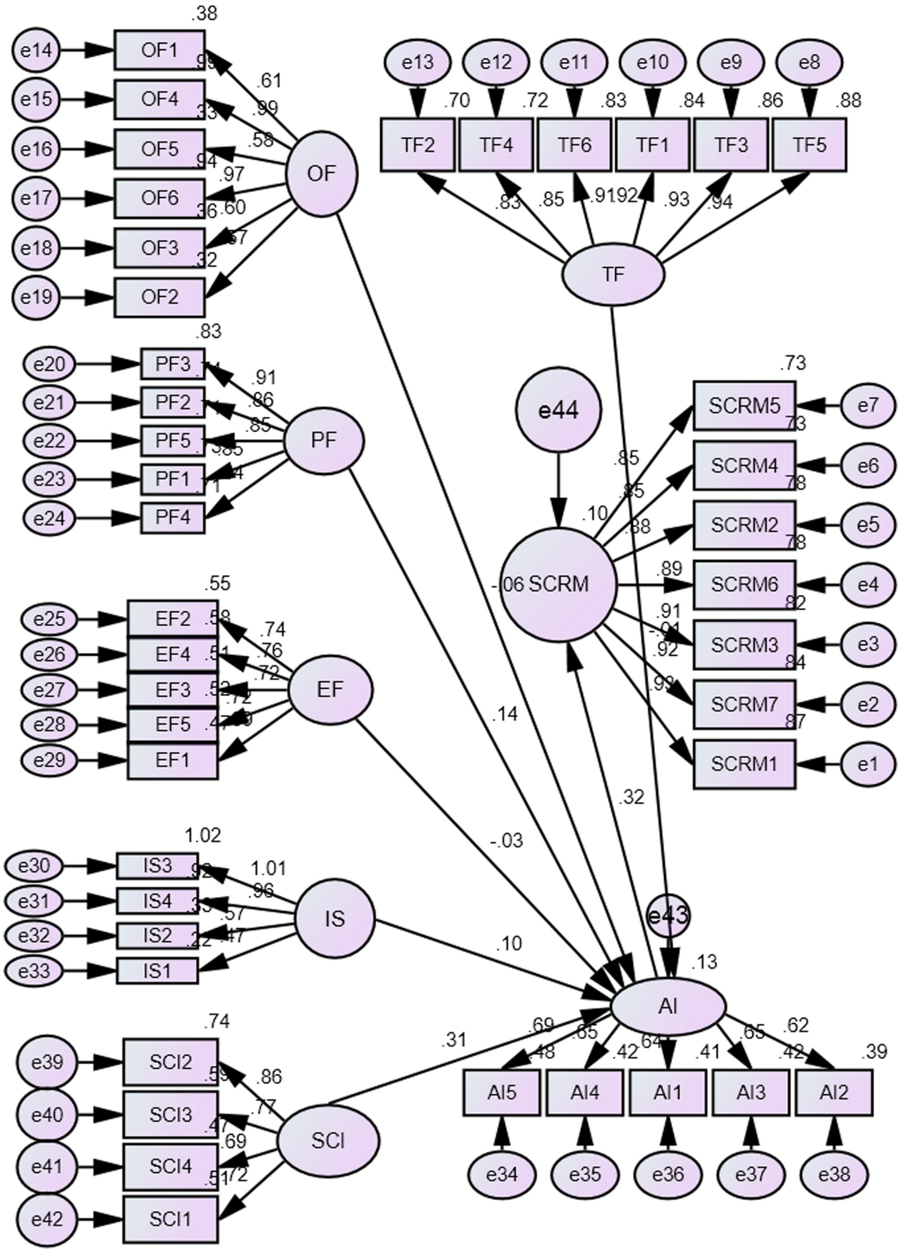

Figure 2.
SEM path diagram

(Cubric, 2020; Di Vaio *et al.*, 2020). Machine and equipment reliability can be improved with the intelligence supported by automated AI-system implementation (Dwivedi *et al.*, 2019), which will reduce the risk of machine and equipment breakdown. Thus, AI helps mitigate the risks caused by SC disruptions through cost reduction, enhanced traceability, reduced hitches of delivery and breakdown of machines and equipment, improved product quality and assuring product availability.

The positive relation of SC integration on artificial intelligence (H6) received the maximum support after H7 in the proposed model. Chaudhuri *et al.* (2020) stated that SCI could positively affect SC risk management by developing risk planning competencies in coordination with SC players. SCI involves integrating all interorganizational resources, physical and information integration, socio-relational and techno-process integration of SC players. The SCI plays a significant role in SC's effective responsiveness (Can Saglam *et al.*, 2020; Lezoche *et al.*, 2020). With the need for data integration to share information in real-time, an effective emergent technology implementation must generate quality information to predict dynamic patterns of the market and environment (Dwivedi *et al.*, 2019; Min, 2010). Thus, an efficient SCI pushes AI implementation in AI. In the previous studies about models of emerging technologies, SCI's findings play an important positive role in implementing AI. The customers, suppliers and manufacturers may opine that AI intelligence can solve good quality and efficient information sharing. As one of the AI techniques, the Bayesian network can combine multiple information sources (Uusitalo, 2007) to identify the risk factors at SC nodes having disruptions simultaneously (Ojha *et al.*, 2018).

The process factor positively influencing artificial intelligence was the second hypothesis that was significantly supported in the test. How AI helps in dealing with the process risks associated with SC disruptions is discussed with the help of available literature, which can justify the positive relationship between AI and process factors. The execution of Industry 4.0 technologies improves productivity and provides better working conditions, leading to workers' retention and attraction. The use of digital technologies enables traceability, and thus, quality management while optimizing SC (Panetto *et al.*, 2019). Sharing information through AI helps maintain quality at an acceptable level (Rodríguez-Espíndola *et al.*, 2020), e.g. the image processing-based pasta defect and predictive maintenance (Massaro and Galiano, 2020). The product design and customization may be possible with AI techniques. Expert system application in SC is considered useful for product design (Min, 2010) and agent-based modeling for mass customization in the e-commerce business (Turowski, 2002). Automating the SC process will compensate for the shortage of labor (Lezoche *et al.*, 2020) and reduce operators' workload (Dwivedi *et al.*, 2019). The AI-enabled conversational interface can help align all SC activities and players for sharing information (Dwivedi *et al.*, 2019). The AI techniques based on machine learning help inventory management and control by improving demand forecasting (Min, 2010). Technology giants like Amazon and Walmart are also exploring AI with data analytics and sensor technologies for demand forecasting and SC fulfillment (Forbes, 2019).

The third hypothesis that information sharing positively influences artificial intelligence was also significantly supported by the SEM analysis. The focal firm and its SC partners generally share information about performance metrics, demand forecasts, production and delivery schedules, and inventory and sales data (Novais *et al.*, 2020). Information sharing technology also plays a critical role in maintaining the SC's competitiveness and efficiency

Table 5.
Results of mediation effect

Relationship	Direct effect	Indirect effect	Result
TF→AI→SCRM	−0.024 (0.664)	0.000 (0.972)	–
EF→AI→SCRM	0.000 (0.994)	−0.006 (0.653)	–
IS→AI→SCRM	*0.120 (0.083)	0.023 (0.136)	–
SCI→AI→SCRM	−0.064 (0.378)	*0.071 (0.001)	Full mediation
OF→AI→SCRM	−0.007 (0.885)	−0.004 (0.814)	–
PF→AI→SCRM	0.060 (0.238)	*0.032 (0.051)	Full mediation

Note(s): * Correlation is significant at the 0.05 level (2-tailed)

(Subramanian *et al.*, 2015). Papadopoulos *et al.* (2017) and Lezoche *et al.* (2020) reported quality information sharing as one of the enablers for risk mitigation, resilience and responsiveness. Firms can extract valuable insights and information for business decisions via AI integration with big data in the complex and heterogeneous business environment (Zhong *et al.*, 2017). AI proved to be a useful decision-making technology, especially ML techniques, namely, artificial neural network (ANN), agent-based system and expert system, which help in efficient inventory planning and control, demand forecasting, inventory handling, transparent handling and deployment of resources and prediction of bullwhip effect by enabling accurate and real-time information exchange among SC partners (Min, 2010; Rodríguez-Espíndola *et al.*, 2020; Bottani *et al.*, 2019).

Technological factors, organizational factors and environmental factors were those for which the hypotheses (H1, H2, H4) were rejected in SEM analysis. The relationship of organizational factors is in support of the result of Wong *et al.* (2020). The immaturity of technology can cause an insignificant relationship between organizational factors and AI (Dwivedi *et al.*, 2019; Cubric, 2020). Maybe the managers do not know the interorganizational barrier, cost and degree of management support required for AI implementation because they have not experienced it before. However, the technology factor hypotheses are against the result of Wong *et al.* (2020). The users or practitioners have insufficient knowledge about the benefits of AI technologies (Sun and Medaglia, 2019; Cubric, 2020), perhaps because of a lack of knowledge transmission from the academy to the SME industry (Lezoche *et al.*, 2020) and a lack of estimation for adjustments between differentiation and commercialization of AI (Dwivedi *et al.*, 2019). The AI has been hyped in recent years and lacks empirical and technical evidence of profitability through its application (Dwivedi *et al.*, 2019). AI systems still need to explore much on developing human intelligence, making AI implementation vulnerable to many situations (Mitchell, 2019). Thus, there is a gap in exploring and understanding applicability in terms of technical factors such as data quality requirements, network complexity (Cichosz *et al.*, 2020), standardization and regulation, and technology availability to support the AI ecosystem. Dwivedi *et al.* (2019) also reported that leaders seem to react slowly to technological changes, which indicates a knowledge gap. However, the environmental factor partially supports the findings of Wong *et al.* (2020). The reason behind this can be the consideration of different subfactors and items. The reason for the rejection of the environment factor hypothesis is that the managers prioritize risk disruption rather than focussing on the surrounding condition's role in affecting AI implementation.

No previous study has explored AI adoption and risk mitigation factors. Therefore, the model can be explored for different geographies for more realistic and accurate findings, with variations in factors or other sectors. Our study with the proposed model lays the foundation for future, cutting-edge empirical research in AI adoption and ASC risk management.

7. Conclusion, implications and limitations

7.1 Conclusion

This study explored the factors affecting artificial intelligence application for supply chain risk mitigation in India's agriculture sector. Various authors have explored SC risk management with AI techniques, conceptual framework, mathematical modeling, simulation and literature. However, no one has studied the role of factors in influencing AI implementation and AI effect on SC risk mitigation. Many authors have emphasized digitalization for mitigating the SC risks caused by uncertain disruptions like COVID-19. Firms are looking for innovative and advanced technologies to mitigate SC risks. Therefore, it is essential to study the feasible AI implementation factors and their impact on SC risk mitigation. This study formulates a theory on AI, which presents the effect of various factors on AI adoption based on the TOE framework and OIPT and outlines the positive impact of AI on supply chain risk mitigation.

The proposed conceptual model identified six factors affecting AI adoption. The proposed AI model was validated through a survey of the Indian agriculture sector's SMEs by utilizing SEM. The model also validates the relationship between AI and SC risk mitigation. In Indian ASC, the suitability of AI implementation with empirical proof is still in its infancy. However, various technology service providers and government organizations have explored AI technology usage at the farm level to increase crop yield and reduce environmental risks. This study helps SC players, technology service providers, policymakers and the government understand the factors affecting AI adoption and realize the importance of AI in SC risk mitigation.

7.2 Theoretical implications

Our study empirically explored factors affecting two managerial concepts together, AI adoption and AI effect on supply chain risk management. No other study has explored AI for SC risk mitigation in the agriculture sector. This study lays the foundation for exploring AI potential and suitability for SCRM. This study explains the relationships and interactions between AI and SCRM with a developed model based on the TOE framework and OIPT with necessary alterations. This study also provides significant insights to the researchers on factors affecting AI to extend the list of factors further and check the feasibility of AI adoption in ASC. The research findings provide empirical evidence for the mediating role of AI adoption for supply chain risk mitigation by considering six factors: technology factors, organizational factors, environmental factors, process factors, supply chain integration and information sharing. The researchers can also develop an AI business model under logistics 4.0 to manage risks in uncertain situations like the COVID-19 pandemic. Food wastage is one of the risks of ASC in COVID-19. Thus, for reducing food wastage, researchers can extend this research work by developing SC models by empirically exploring AI benefits and capabilities such as advanced predictive analytics, expert system, demand forecasting, error reduction, etc.

7.3 Managerial implications

AI-enabled industry 4.0 system helps analyze and get value with AI techniques like big data analytics, machine learning and deep learning from collected data from cloud computing through IoT devices, connecting and exchanging data within devices in a network over the Internet. AI can positively influence ASC risk mitigation in a pandemic situation like COVID-19 by improving decision-making through advanced predictive analytics, expert system and error reduction. AI advantages and benefits to improve flexibility, responsiveness, resilience and robustness may improve SC risk mitigation performance. This research paper provides evidence to managers of the significant role of AI in enhancing SCRM. This study also provides an understanding of the factors influencing AI adoption in ASC. Supply chain integration is the most critical factor in influencing AI adoption. Thus, managers need to share information and knowledge with the suppliers, customers and employees within an organization and among stakeholders. This study also shows that information sharing positively affects AI and AI affects SCRM; thus, SC risk mitigation can be achieved smoothly by improving information-sharing technology and quality. The AI-enabled logistics 4.0 system enhances decision-making by improving information quality and sharing, which can help improve resource utilization, efficiency and productivity. This study also suggests that managers need to focus on SC process factors for speeding up AI adoption after supply chain integration and information sharing. Therefore, successful AI adoption managers and innovative project handlers need to focus more on integrating the SC by improving information quality and efficient information-sharing technology. The technology service providers need to provide solutions through AI implementation in SC for information technology (IT)-interface problems, inventory control, quality issues, product design and customization, employee workload and labor shortage. Its ability of real-time information sharing, traceability, continuous monitoring, maintaining product quality and availability help reduce food wastage and minimize resource utilization, thus promoting a green supply chain. Therefore, this study provides valuable insights for policymakers, managers, innovative project handlers and technology service providers.

7.4 Future scope or limitations

Sometimes, survey-based data collection can create response bias based on professionals' response, which varies from one to another based on their experience, culture, industry and understanding. Therefore, the results of this study related to the acceptance and rejection of hypotheses are not universal. The researchers can extend the study on AI: (1) Data sample size can be increased to get more generalized findings. (2) The same study can be extended based on the unified theory of acceptance and technology use (UTAUT) theory and the technology acceptance model (TAM). (3) Process factors, SCI and information sharing can be explored by adjusting these in technology, environment and organizational factors, following their suitability. (4) The role of advantages and benefits of AI in SCRM can be explored (5). For getting more realistic and generalized findings, the same model can be validated by surveying a different sector. (6) The moderating role of top management support and trust for the relationship between AI and SCRM can be studied in the same model.

References

Abdallah, A.B. and Nabass, I.H. (2018), "Supply chain antecedents of agile manufacturing in a developing country context: an empirical investigation", *Journal of Manufacturing Technology Management*, Vol. 29 No. 6, pp. 1042-1064.

Agrawal, A., Gans, J. and Goldfarb, A. (2017), "What to expect from artificial intelligence?", *MIT Sloan Management Review*, Vol. 58 No. 3, pp. 22-27.

Ahire, S.L., Golhar, D.Y. and Waller, M.A. (1996), "Development and validation of TQM implementation constructs", *Decision Sciences*, Vol. 27, pp. 23-56.

Araz, O.M., Choi, T.M., Olson, D. and Salman, F.S. (2020), "Data analytics for operational risk management", *Decision Sciences*, Vol. 51 No. 6, pp. 1316-1319.

Armstrong, J.S. and Overton, T.S. (1977), "Estimating nonresponse bias in mail surveys", *Journal of Marketing Research*, Vol. 14 No. 3, pp. 396-402.

Astill, J., Dara, R.A., Campbell, M., Farber, J.M., Fraser, E.D., Sharif, S. and Yada, R.Y. (2019), "Transparency in food supply chains: a review of enabling technology solutions", *Trends in Food Science and Technology*, Vol. 91, pp. 240-247.

Awa, H.O., Uko, J.P. and Ukoha, O. (2017), "An empirical study of some critical adoption factors of ERP software", *International Journal of Human-computer Interaction*, Vol. 33 No. 8, pp. 609-622.

Azad, N., Davoudpour, H., Saharidis, G.K. and Shiripour, M. (2014), "A new model to mitigating random disruption risks of facility and transportation in supply chain network design", *International Journal of Advanced Manufacturing Technology*, Vol. 70 Nos 9-12, pp. 1757-1774.

Bag, S., Pretorius, J.H.C., Gupta, S. and Dwivedi, Y.K. (2020), "Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities", *Technological Forecasting and Social Change*, Vol. 163 No. C, 120420.

Bagozzi, R.P. and Yi, Y. (2012), "Specification, evaluation, and interpretation of structural equation models", *Journal of the Academy of Marketing Science*, Vol. 40 No. 1, pp. 8-34.

Barth, H., Ulvenblad, P.O. and Ulvenblad, P. (2017), "Towards a conceptual framework of sustainable business model innovation in the agri-food sector: a systematic literature review", *Sustainability*, Vol. 9 No. 9, p. 1620.

Baryannis, G., Dani, S. and Antoniou, G. (2019a), "Predicting supply chain risks using machine learning: the trade-off between performance and interpretability", *Future Generation Computer Systems*, Vol. 101, pp. 993-1004.

Baryannis, G., Validi, S., Dani, S. and Antoniou, G. (2019b), "Supply chain risk management and artificial intelligence: state of the art and future research directions", *International Journal of Production Research*, Vol. 57 No. 7, pp. 2179-2202.

Betti, F. and Ni, J. (2020), "How China can rebuild global supply chain resilience after COVID-19", *World Economic Forum*, available at: https://www.wefor um.org/.

Blos, M.F., da Silva, R.M. and Wee, H.M. (2018), "A framework for designing supply chain disruptions management considering productive systems and carrier viewpoints", *International Journal of Production Research*, Vol. 56 No. 15, pp. 5045-5061.

Bottani, E., Centobelli, P., Gallo, M., Kaviani, M.A., Jain, V. and Murino, T. (2019), "Modelling wholesale distribution operations: an artificial intelligence framework", *Industrial Management and Data Systems*, Vol. 119 No. 4, pp. 698-718.

Çankaya, S.Y. (2020), "The effects of strategic sourcing on supply chain strategies", *Journal of Global Operations and Strategic Sourcing*, Vol. 13 No. 2, pp. 129-148.

Carr, A.S. and Kaynak, H. (2007), "Communication methods, information sharing, supplier development and performance", *International Journal of Operations and Production Management*, Vol. 27 No. 4, pp. 346-370.

Chang, W., Ellinger, A.E. and Blackhurst, J. (2015), "A contextual approach to supply chain risk mitigation", *International Journal of Logistics Management*, Vol. 26 No. 3, pp. 642-656.

Chaudhuri, A., Ghadge, A., Gaudenzi, B. and Dani, S. (2020), "A conceptual framework for improving effectiveness of risk management in supply networks", *International Journal of Logistics Management*, Vol. 31 No. 1, pp. 77-98.

Chesbrough, H. (2020), "To recover faster from Covid-19, open up: managerial implications from an open innovation perspective", *Industrial Marketing Management*, Vol. 88, pp. 410-413.

Chiarini, A., Belvedere, V. and Grando, A. (2020), "Industry 4.0 strategies and technological developments. An exploratory research from Italian manufacturing companies", *Production Planning and Control*, Vol. 31 No. 16, pp. 1385-1398.

Chowdhury, M.T., Sarkar, A., Paul, S.K. and Moktadir, M.A. (2020), "A case study on strategies to deal with the impacts of COVID-19 pandemic in the food and beverage industry", *Operations Management Research*, doi: 10.1007/s12063-020-00166-9.

Cichosz, M., Wallenburg, C.M. and Knemeyer, A.M. (2020), "Digital transformation at logistics service providers: barriers, success factors and leading practices", *International Journal of Logistics Management*, Vol. 31 No. 2, pp. 209-238.

Coulibaly, S., Kamsu-Foguem, B., Kamissoko, D. and Traore, D. (2019), "Deep neural networks with transfer learning in millet crop images", *Computers in Industry*, Vol. 108, pp. 115-120.

Cubric, M. (2020), "Drivers, barriers and social considerations for AI adoption in business and management: a tertiary study", *Technology in Society*, Vol. 62, p. 101257.

Daft, R.L., Lengel, R.H. and Trevino, L.K. (1987), "Message equivocality, media selection, and manager performance: implications for information systems", *MIS Quarterly*, Vol. 11 No. 3, pp. 355-366.

Dash, M., Shadangi, P.Y., Muduli, K.K., Luhach, A.K. and Mohamed, A. (2021), "Predicting the motivators of telemedicine acceptance in COVID-19 pandemic using multiple regression and ANN approach", *Journal of Statistics and Management Systems*, Vol. 24 No. 2, pp. 319-339.

Dhamija, P. and Bag, S. (2020), "Role of artificial intelligence in operations environment: a review and bibliometric analysis", *The Total Quality Management Journal*, Vol. 32 No. 4, pp. 869-896.

Di Vaio, A., Boccia, F., Landriani, L. and Palladino, R. (2020), "Artificial intelligence in the agri-food system: rethinking sustainable business models in the COVID-19 scenario", *Sustainability*, Vol. 12 No. 12, p. 4851.

Doherty, S. and Botwright, K. (2020), "What past disruptions can teach us about reviving supply chains after COVID-19", *World Economic Forum*, available at: https ://www.wefor um.org/.

Dubey, R., Gunasekaran, A., Childe, S.J., Bryde, D.J., Giannakis, M., Foropon, C. and Hazen, B.T. (2020), "Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: a study of manufacturing organisations", *International Journal of Production Economics*, Vol. 226, p. 107599.

Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, R., Eirug, A., Galanos, V., Ilavarasan, P.V., Janssen, M., Jones, P., Kark, A.K., Kizgin, H., Kronemannm, B., Lalf, B., Lucini, B., Medaglia, R., Le Meunier-FitzHugh, K., Le Meunier-FitzHugh, L.C., Misraq, S., Mogaji, E., Sharma, S.K., Singh, J.B., Raghavan, V., Raman, R., Rana, N.P., Samothrakis, S., Spencer, J., Tamilmani, K., Tubadji, A., Walton, P. and Williams, M.D. (2019), "Artificial Intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy", *International Journal of Information Management*, Vol. 57, 101994.

ET CIO (2018), "India ranked third in terms of Artificial Intelligence implementation: report", *The Economic Times*, available at: https://cio.economictimes.indiatimes.com/.

Fan, H., Cheng, T.C.E., Li, G. and Lee, P.K. (2016), "The effectiveness of supply chain risk information processing capability: an information processing perspective", *IEEE Transactions on Engineering Management*, Vol. 63 No. 4, pp. 414-425.

Fan, H., Li, G., Sun, H. and Cheng, T.C.E. (2017), "An information processing perspective on supply chain risk management: antecedents, mechanism, and consequences", *International Journal of Production Economics*, Vol. 185, pp. 63-75.

Fernandes, K. (2020), "Artificial intelligence in agriculture in India", *The CSR Journal*, available at: https://thecsrjournal.in/.

Fornell, C. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research*, Vol. 18 No. 1, pp. 39-50.

Galbraith, J. (1973), *Designing Complex Organizations*, Mass, Reading.

Garvey, M.D., Carnovale, S. and Yeniyurt, S. (2015), "An analytical framework for supply network risk propagation: a Bayesian network approach", *European Journal of Operational Research*, Vol. 243 No. 2, pp. 618-627.

Gefen, D., Straub, D. and Boudreau, M.C. (2000), "Structural equation modeling and regression: guidelines for research practice", *Communications of the Association for Information Systems*, Vol. 4 No. 1, p. 7.

Gerbing, D.W. and Anderson, J.C. (1988), "An updated paradigm for scale development incorporating unidimensionality and its assessment", *Journal of Marketing Research*, Vol. 25 No. 2, pp. 186-192.

Goddard, E. (2020), "The impact of COVID-19 on food retail and food service in Canada: preliminary assessment", *Canadian Journal of Agricultural Economics*, Vol. 68 No. 2, pp. 157-161.

Gravili, G., Benvenuto, M., Avram, A. and Viola, C. (2018), "The influence of the Digital Divide on Big Data generation within supply chain management", *International Journal of Logistics Management*, Vol. 29 No. 2, pp. 592-628.

Hair, J.F., Black, W.C., Babin, B.J. and Anderson, R.E. (2009), *Multivariate Data Analysis*, Prentice Hall, New Jersey.

Hair, J.F., Ringle, C.M. and Sarstedt, M. (2011), "PLS-SEM: indeed a silver bullet", *Journal of Marketing Theory and Practice*, Vol. 19 No. 2, pp. 139-152.

Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M. and Thiele, K.O. (2017), "Mirror, mirror on the wall: a comparative evaluation of composite-based structural equation modeling methods", *Journal of the Academy of Marketing Science*, Vol. 45 No. 5, pp. 616-632.

Hosseini, S., Ivanov, D. and Dolgui, A. (2019), "Review of quantitative methods for supply chain resilience analysis", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 125, pp. 285-307.

Ivanov, D. (2020a), "Predicting the impacts of epidemic outbreaks on global supply chains: a simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 136, p. 101922.

Ivanov, D. (2020b), "Viable supply chain model: integrating agility, resilience and sustainability perspectives—lessons from and thinking beyond the COVID-19 pandemic", *Annals of Operations Research*, pp. 1-21.

Ivanov, D. and Dolgui, A. (2020), "A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0", *Production Planning and Control*, pp. 1-14.

Ivanov, D., Dolgui, A. and Sokolov, B. (2019), "The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics", *International Journal of Production Research*, Vol. 57 No. 3, pp. 829-846.

Kara, M.E., Fırat, S.Ü.O. and Ghadge, A. (2020), "A data mining-based framework for supply chain risk management", *Computers and Industrial Engineering*, Vol. 139, p. 105570.

Ker, A.P. and Cardwell, R. (2020), "Introduction to the special issue on COVID-19 and the Canadian agriculture and food sectors: thoughts from the pandemic onset", *Canadian Journal of Agricultural Economics*, Vol. 68 No. 2, pp. 139-142.

Kim, M. and Chai, S. (2017), "The impact of supplier innovativeness, information sharing and strategic sourcing on improving supply chain agility: global supply chain perspective", *International Journal of Production Economics*, Vol. 187, pp. 42-52.

Kumar, S. and Managi, S. (2020), "Does stringency of lockdown affect air quality? Evidence from Indian cities", *Economics of Disasters and Climate Change*, Vol. 4 No. 3, pp. 481-502.

Kumar, A., Mangla, S.K., Kumar, P. and Song, M. (2021a), "Mitigate risks in perishable food supply chains: learning from COVID-19", *Technological Forecasting and Social Change*, Vol. 166, p. 120643.

Kumar, S., Raut, R.D., Nayal, K., Kraus, S., Yadav, V.S. and Narkhede, B.E. (2021b), "To identify industry 4.0 and circular economy adoption barriers in the agriculture supply chain by using ISM-ANP", *Journal of Cleaner Production*, Vol. 293, p. 126023.

L'Hermitte, C., Tatham, P., Brooks, B. and Bowles, M. (2016), "Supply chain agility in humanitarian protracted operations", *Journal of Humanitarian Logistics and Supply Chain Management*, Vol. 6 No. 2, pp. 173-201.

Laborde, D., Martin, W., Swinnen, J. and Vos, R. (2020), "COVID-19 risks to global food security", *Science*, Vol. 369 No. 6503, pp. 500-502.

Lai, Y., Sun, H. and Ren, J. (2018), "Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management", *International Journal of Logistics Management*, Vol. 29 No. 2, pp. 676-703.

Lezoche, M., Hernandez, J.E., Díaz, M.D.M.E.A., Panetto, H. and Kacprzyk, J. (2020), "Agri-food 4.0: a survey of the supply chains and technologies for the future agriculture", *Computers in Industry*, Vol. 117, p. 103187.

Li, S., Rao, S.S., Ragu-Nathan, T.S. and Ragu-Nathan, B. (2005), "Development and validation of a measurement instrument for studying supply chain management practices", *Journal of Operations Management*, Vol. 23 No. 6, pp. 618-641.

Liu, C.L. and Lee, M.Y. (2018), "Integration, supply chain resilience, and service performance in third-party logistics providers", *International Journal of Logistics Management*, Vol. 29 No. 1, pp. 5-21.

Liu, X., Arthanari, T. and Shi, Y. (2019), "Making dairy supply chains robust against corruption risk: a systemic exploratory study", *International Journal of Logistics Management*, Vol. 30 No. 4, pp. 1078-1100.

Liu, Y., Ma, X., Shu, L., Hancke, G.P. and Abu-Mahfouz, A.M. (2020), "From industry 4.0 to agriculture 4.0: current status, enabling technologies, and research challenges", *IEEE Transactions on Industrial Informatics*, Vol. 17 No. 6, available at: http://hdl.handle.net/10204/11981.

Loeb, W. (2019), "Walmart unveils a new lab store that uses AI", *Forbes*, available at: https://www.forbes.com/.

Lowry, P.B. and Gaskin, J. (2014), "Partial least squares (PLS) structural equation modeling (SEM) for building and testing behavioral causal theory: when to choose it and how to use it", *EEE Transactions on Professional Communication*, Vol. 57 No. 2, pp. 123-146.

Luthra, S. and Mangla, S.K. (2018), "Evaluating challenges to Industry 4.0 initiatives for supply chain sustainability in emerging economies", *Process Safety and Environmental Protection*, Vol. 117, pp. 168-179.

Mandal, S. (2017), "The influence of organizational culture on healthcare supply chain resilience: moderating role of technology orientation", *The Journal of Business and Industrial Marketing*, Vol. 32 No. 8, pp. 1021-1037.

Mandal, S. (2020), "Impact of supplier innovativeness, top management support and strategic sourcing on supply chain resilience", *International Journal of Productivity and Performance Management*, Vol. ahead-of-print No. ahead-of-print, doi: 10.1108/IJPPM-07-2019-0349.

Massaro, A. and Galiano, A. (2020), "Re-engineering process in a food factory: an overview of technologies and approaches for the design of pasta production processes", *Production and Manufacturing Research*, Vol. 8 No. 1, pp. 80-100.

McEwan, K., Marchand, L., Shang, M. and Bucknell, D. (2020), "Potential implications of COVID-19 on the Canadian pork industry", *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, Vol. 68 No. 2, pp. 201-206.

Merschmann, U. and Thonemann, U.W. (2011), "Supply chain flexibility, uncertainty and firm performance: an empirical analysis of German manufacturing firms", *International Journal of Production Economics*, Vol. 130 No. 1, pp. 43-53.

Min, H. (2010), "Artificial intelligence in supply chain management: theory and applications", *International Journal of Logistics: Research and Applications*, Vol. 13 No. 1, pp. 13-39.

Mitchell, M. (2019), "Artificial intelligence hits the barrier of meaning", *Information*, Vol. 10 No. 2, p. 51.

Mohtaramzadeh, M., Ramayah, T. and Cheah, J.H. (2018), "B2B E-Commerce adoption in iranian manufacturing companies: analyzing the moderating role of organizational culture", *International Journal of Human-computer Interaction*, Vol. 34 No. 7, pp. 621-639.

Muduli, K.K., Luthra, S., Kumar Mangla, S., Jabbour, C.J.C., Aich, S. and de Guimarães, J.C.F. (2020), "Environmental management and the "soft side" of organisations: discovering the most relevant behavioural factors in green supply chains", *Business Strategy and the Environment*, Vol. 29 No. 4, pp. 1647-1665.

Narwane, V.S., Raut, R.D., Mangla, S.K., Gardas, B.B., Narkhede, B.E., Awasthi, A. and Priyadarshinee, P. (2020), "Mediating role of cloud of things in improving performance of small and medium enterprises in the Indian context", *Annals of Operations Research*, pp. 1-30.

Nayak, A., Lokesha, H., Shariff, M. and Khan, M. (2019), "The Economics of applications of artificial intelligence and machine learning in agriculture", *International Journal of Pure Applied Bioscience*, Vol. 7 No. 1, pp. 296-305.

Nguyen, T., Li, Z.H.O.U., Spiegler, V., Ieromonachou, P. and Lin, Y. (2018), "Big data analytics in supply chain management: a state-of-the-art literature review", *Computers and Operations Research*, Vol. 98, pp. 254-264.

Novais, L., Marín, J.M.M. and Moyano-Fuentes, J. (2020), "Lean production implementation, cloud-supported logistics and supply chain integration: interrelationships and effects on business performance", *International Journal of Logistics Management*, Vol. 31 No. 3, pp. 629-663.

Nunnally, J.C. (1978), *Psychometric Theory*, McGraw-Hill book company, New York.

Ojha, R., Ghadge, A., Tiwari, M.K. and Bititci, U.S. (2018), "Bayesian network modelling for supply chain risk propagation", *International Journal of Production Research*, Vol. 56 No. 17, pp. 5795-5819.

Panetto, H., Iung, B., Ivanov, D., Weichhart, G. and Wang, X. (2019), "Challenges for the cyber-physical manufacturing enterprises of the future", *Annual Reviews in Control*, Vol. 47, pp. 200-213.

Papadopoulos, T., Gunasekaran, A., Dubey, R. and Fosso Wamba, S. (2017), "Big data and analytics in operations and supply chain management: managerial aspects and practical challenges", *Production Planning and Control*, Vol. 28 Nos 11-12, pp. 873-876.

Podsakoff, P.M. and Organ, D.W. (1986), "Self-reports in organizational research: problems and prospects", *Journal of Management*, Vol. 12 No. 4, pp. 531-544.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y. and Podsakoff, N.P. (2003), "Common method biases in behavioral research: a critical review of the literature and recommended remedies", *Journal of Applied Psychology*, Vol. 88 No. 5, pp. 879-903.

Remko, V.H. (2020), "Research opportunities for a more resilient post-COVID-19 supply chain–closing the gap between research findings and industry practice", *International Journal of Operations and Production Management*, Vol. 40 No. 4, pp. 341-355.

Rodríguez-Espíndola, O., Chowdhury, S., Beltagui, A. and Albores, P. (2020), "The potential of emergent disruptive technologies for humanitarian supply chains: the integration of blockchain, Artificial Intelligence and 3D printing", *International Journal of Production Research*, Vol. 58 No. 15, pp. 4610-4630.

Can Saglam, Y., Yildiz Çankaya, S. and Sezen, B. (2020), "Proactive risk mitigation strategies and supply chain risk management performance: an empirical analysis for manufacturing firms in Turkey", *Journal of Manufacturing Technology Management*, Vol. ahead-of-print No. ahead-of-print, doi: 10.1108/JMTM-08-2019-0299.

Serazetdinova, L., Garratt, J., Baylis, A., Stergiadis, S., Collison, M. and Davis, S. (2019), "How should we turn data into decisions in AgriFood?", *Journal of the Science of Food and Agriculture*, Vol. 99 No. 7, pp. 3213-3219.

Shang, Y., Dunson, D. and Song, J.S. (2017), "Exploiting big data in logistics risk assessment via bayesian non parametrics", *Operations Research*, Vol. 65 No. 6, pp. 1574-1588.

Sharma, R., Shishodia, A., Kamble, S., Gunasekaran, A. and Belhadi, A. (2020), "Agriculture supply chain risks and COVID-19: mitigation strategies and implications for the practitioners", *International Journal of Logistics Research and Applications*, pp. 1-27.

Singh, A. (2020), "AI for farmer", *The Indian Express*, available at: https://indianexpress.com/.

Singh, S., Kumar, R., Panchal, R. and Tiwari, M.K. (2020), "Impact of COVID-19 on logistics systems and disruptions in food supply chain", *International Journal of Production Research*, pp. 1-16.

Skulmoski, G.J., Hartman, F.T. and Krahn, J. (2007), "The Delphi method for graduate research", *Information Technology Education: Research: Ideas for Today's Investors*, Vol. 6 No. 1, pp. 1-21.

Srinivasan, R. and Swink, M. (2018), "An investigation of visibility and flexibility as complements to supply chain analytics: an organizational information processing theory perspective", *Production and Operations Management*, Vol. 27 No. 10, pp. 1849-1867.

Subramanian, N. and Abdulrahman, M.D. (2017), "Logistics and cloud computing service providers' cooperation: a resilience perspective", *Production Planning and Control*, Vol. 28 Nos 11-12, pp. 919-928.

Subramanian, N., Abdulrahman, M.D. and Zhou, X. (2015), "Reprint of "Integration of logistics and cloud computing service providers: cost and green benefits in the Chinese context", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 74, pp. 81-93.

Sun, T.Q. and Medaglia, R. (2019), "Mapping the challenges of artificial intelligence in the public sector: evidence from public healthcare", *Government Information Quarterly*, Vol. 36 No. 2, pp. 368-383.

Tornatzky, L.G., Fleischer, M. and Chakrabarti, A.K. (1990), *The Process of Technological Innovation*, Lexington Books, Lexington, MA.

Turowski, K. (2002), "Agent-based e-commerce in case of mass customization", *International Journal of Production Economics*, Vol. 75 Nos 1-2, pp. 69-81.

Tushman, M.L. and Nadler, D.A. (1978), "Information processing as an integrating concept in organizational design", *Academy of Management Review*, Vol. 3 No. 3, pp. 613-624.

Uusitalo, L. (2007), "Advantages and challenges of Bayesian networks in environmental modelling", *Ecological Modelling*, Vol. 203 Nos 3-4, pp. 312-318.

Vishnu, C.R., Sridharan, R., Gunasekaran, A. and Kumar, P.R. (2019), "Strategic capabilities for managing risks in supply chains: current state and research futurities", *Journal of Advances in Management Research*, Vol. 17 No. 2, pp. 173-211.

Wang-Mlynek, L. and Foerstl, K. (2020), "Barriers to multi-tier supply chain risk management", *International Journal of Logistics Management*, Vol. 31 No. 3, pp. 465-487.

Wong, L.W., Leong, L.Y., Hew, J.J., Tan, G.W.H. and Ooi, K.B. (2020), "Time to seize the digital evolution: adoption of blockchain in operations and supply chain management among Malaysian SMEs", *International Journal of Information Management*, Vol. 52, p. 101997.

Yao, X., Huang, R., Song, M. and Mishra, N. (2018), "Pre-positioning inventory and service outsourcing of relief material supply chain", *International Journal of Production Research*, Vol. 56 No. 21, pp. 6859-6871.

Ye, S., Xiao, Z. and Zhu, G. (2015), "Identification of supply chain disruptions with economic performance of firms using multi-category support vector machines", *International Journal of Production Research*, Vol. 53 No. 10, pp. 3086-3103.

Zhang, Y., Baker, D. and Griffith, G. (2020), "Product quality information in supply chains: a performance-linked conceptual framework applied to the Australian red meat industry", *International Journal of Logistics Management*, Vol. 31 No. 3, pp. 697-723.

Zhong, R.Y., Xu, C., Chen, C. and Huang, G.Q. (2017), "Big data analytics for physical internet-based intelligent manufacturing shop floors", *International Journal of Production Research*, Vol. 55 No. 9, pp. 2610-2621.

Annexure

		N	Correlation	Sig
Pair 1	SCRM1_E and SCRM1_L	108	0.117	0.230
Pair 2	SCRM2_E and SCRM2_L	108	0.094	0.334
Pair 3	SCRM3_E and SCRM3_L	108	0.055	0.573
Pair 4	SCRM4_E and SCRM4_L	108	0.043	0.661
Pair 5	SCRM5_E and SCRM5_L	108	0.092	0.345
Pair 6	SCRM6_E and SCRM6_L	108	0.162	0.094
Pair 7	SCRM7_E and SCRM7_L	108	0.118	0.226
Pair 8	PF1_E and PF1_L	108	0.184	0.056
Pair 9	PF2_E and PF2_L	108	0.155	0.109
Pair 10	PF3_E and PF3_L	108	0.243	0.011
Pair 11	PF4_E and PF4_L	108	0.042	0.669
Pair 12	PF5_E and PF5_L	108	0.188	0.051
Pair 13	AI1_E and AI1_L	108	−0.167	0.084
Pair 14	AI2_E and AI2_L	108	−0.022	0.820
Pair 15	AI3_E and AI3_L	108	0.041	0.673
Pair 16	AI4_E and AI4_L	108	−0.060	0.534
Pair 17	AI5_E and AI5_L	108	−0.211	0.028
Pair 18	OF1_E and OF1_L	108	−0.028	0.777
Pair 19	OF2_E and OF2_L	108	−0.245	0.010
Pair 20	OF3_E and OF3_L	108	−0.078	0.423
Pair 21	OF4_E and OF4_L	108	−0.018	0.853
Pair 22	SCI1_E and SCI1_L	108	0.018	0.856
Pair 23	SCI2_E and SCI2_L	108	0.005	0.957
Pair 24	SCI3_E and SCI3_L	108	0.044	0.649
Pair 25	SCI4_E and SCI4_L	108	0.090	0.357
Pair 26	IS1_E and IS1_L	108	−0.114	0.240
Pair 27	IS2_E and IS2_L	108	0.051	0.600
Pair 28	IS3_E and IS3_L	108	0.094	0.333
Pair 29	IS4_E and IS4_L	108	0.129	0.183
Pair 30	EF1_E and EF1_L	108	0.009	0.925
Pair 31	EF2_E and EF2_L	108	0.193	0.046
Pair 32	EF3_E and EF3_L	108	0.112	0.250
Pair 33	EF4_E and EF4_L	108	−0.072	0.459
Pair 34	EF5_E and EF5_L	108	−0.054	0.576
Pair 35	TF1_E and TF1_L	108	−0.086	0.377
Pair 36	TF2_E and TF2_L	108	−0.087	0.371
Pair 37	TF3_E and TF3_L	108	−0.042	0.669
Pair 38	TF4_E and TF4_L	108	0.022	0.821
Pair 39	TF5_E and TF5_L	108	0.125	0.198
Pair 40	TF6_E and TF6_L	108	0.001	0.990
Pair 41	OF5_E and OF5_L	108	0.046	0.634
Pair 42	OF6_E and OF6_L	108	0.063	0.518

Table A1. Paired samples correlations

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