Journal of Infrastructure, Policy and Development 2025, 9(1), 10114.
https://doi.org/10.24294/jipd10114

Article

Leveraging predictive analytics to enhance food safety risk management in supply chains: A conceptual framework

Reason Masengu[1,*], Chenjerai Muchenje[2,*], Benson Ruzive[3,*]

[1] Department of Management Studies, Middle East College, Muscat 124, Oman
[2] Department of Lifelong Learning, Southeast Technological University, R93 V960 Carlow, Ireland
[3] Department of Business and Economics, Modern College of Business and Science, Muscat 133, Oman
*** Corresponding authors:** Reason Masengu, masengu@mec.edu.om; Chenjerai Muchenje, chenmuchie@gmail.com; Benson Ruzive, Benson.Ruzive@mcbs.edu.om

CITATION

Masengu R, Muchenje C, Ruzive B. (2025). Leveraging predictive analytics to enhance food safety risk management in supply chains: A conceptual framework. Journal of Infrastructure, Policy and Development. 9(1): 10114. https://doi.org/10.24294/jipd10114

ARTICLE INFO

Received: 5 November 2024
Accepted: 3 December 2024
Available online: 6 January 2025

Abstract: Food safety in supply chains remains a critical concern due to the complexity of global distribution networks. This study develops a conceptual framework to evaluate how food safety risks influence supply chain performance through predictive analytics. The framework identifies and minimizes food safety risks before they cause serious problems. The study examines the impact of food safety practices, supply chain transparency, and technological integration on adopting predictive analytics. To illustrate the complex dynamics of food safety and supply chain performance, the study presents supply chain transparency, technological integration, and food safety practices and procedures as independent variables and predictive analytics as a mediator. The results show that supply chain managers' capacity to anticipate and control risks related to food safety can be improved by predictive analytics, leading to safer food production and distribution methods. The research recommends that businesses create scalable cloud-based predictive model solutions, combine data sources, and employ cutting-edge AI and machine learning tools. Companies should also note that strong, data-driven approaches to food safety require cooperative data sharing, regulatory compliance, training initiatives and ongoing improvement.

Keywords: food safety; supply chain performance; predictive analytics; supply chain efficiency

1. Introduction

According to Belhadi et al. (2022), the complexity of Supply Chain (SC) networks affects contamination management and other risks. Rincon-Ballesteros et al. (2024) highlight the potential health risks, financial implications, and regulatory requirements to demonstrate the importance of supply chain management. In the wake of these challenges, this research aims to provide a comprehensive conceptual framework for analyzing how Food Safety Risks (FSR) affect SC efficiency. The global reach of modern food networks has increased the focus on FS in SCs with multiple phases, each presenting challenges (De Boeck et al., 2020). Adulteration, contamination, spoiling, and fraud impact customer health, business reputation, and regulatory compliance (Masengu, Al Habsi, et al., 2024). Reactive approaches are the primary food safety management methods that address issues as they arise. The deleterious impacts of food safety on public health and the economy required reactive approaches to food safety management. Kudashkina et al. (2022) posit that Predictive Analytics (PA) improves SC management by identifying trends to predict future challenges. Kondaveeti et al. (2023) say that a proactive strategy lowers mishaps and improves SC effectiveness, and PA identifies and reduces threats before they become problems. PA also provide insightful analysis and solutions to improve food safety protocols.

This study creates a conceptual framework using PA to correlate (FSR) with Supply Chain Performance (SCP). The framework provides an understanding of how FSR impacts the competitive position, sustainability, and operational efficiency of SCs'. Furthermore, it reflects how SCP is influenced by food safety rules and processes, technology integration, and SC openness (Masengu et al., 2024). The research emphasizes how PA acts as a mediator and improves the ability to control hazards related to food safety. This study provides a framework for improving SC performance through PA. The study aims to close a significant gap in the literature and additionally, practitioners will benefit from PA and recommendations that lead to safer food production and distribution.

Research objectives

- To create a conceptual framework that links food safety risks with supply chain performance through predictive analysis in the Oman food industry.
- To analyze how food safety risks affect supply chain performance in the Oman food industry.
- To analyze how supply chain transparency affects supply chain performance in the Oman food industry.
- To analyze how technological integration affects supply chain performance in the Oman food industry.

Hypothesis

H^1: Food safety practices and procedures influence the adoption of predictive analytics in the Oman food industry.

H^2: Food safety practices and procedures influence the supply chain performance in the Oman Food industry.

H^3: Supply chain performance influences predictive adoption in the Oman food industry.

H^4: Supply transparency influences the adoption of predictive analytics in the Oman food industry.

H^5: Technology Integration influences the adoption of predictive analytics in the Oman food industry.

H^6: Technology integration influences the supply chain performance of the Oman food industry.

H^7: Predictive analytics adoption influences supply chain performance in the Oman food industry.

2. Literature review

With increasing research examining its potential in food safety risk management across supply chains, predictive analytics has become a valuable tool for improving industry decision-making. Modern food supply chains are complicated and globalized, creating difficulties because of the large volume and variety of products, making them more susceptible to contamination and other safety hazards. PA proactively identifies and mitigates to ultimately protect customers and strengthen the supply networks' resilience. This literature review examines prior research on predictive analytics in food safety risk management and highlights important elements, methodological strategies, and weaknesses in the frameworks that could guide a more thorough, data-driven approach to food safety.

2.1. Food safety practices and procedures

Ensuring FS requires implementing rigorous practices and procedures to mitigate risks and maintain the integrity of the food production system. FS practices and procedures protect the public's health, maintain consumer trust, ensure regulatory compliance, prevent financial loss, and improve SC effectiveness (Kamboj et al., 2020). Raspor (2008) says implementing food safety practices and procedures creates a competitive advantage, promotes international trade, reduces risk, promotes sustainability and ensures the health and safety of employees. WHO (2022) estimates that 600 million people are affected by foodborne illnesses annually, resulting in health burdens and economic costs. Effective food safety management mitigates these risks by preventing contamination and ensuring safety standards.

Food safety procedures should be HACCP compliant as they provide a methodical way to identify, assess and manage hazards. Preventive methods reduce the likelihood of food safety problems by focusing on critical control points (Anisatul and Handoko, 2020). While HACCPs protect food from physical, chemical, and biological risks, it is based on the understanding that hazards may occur at different points or stages of production (Ibrahim, 2020). HACCP guarantees the production of high-quality and safe food and supports companies in preventing food safety accidents. It provides hazard identification, assessment and control. HACCP compliance improves food safety, regulatory compliance, customer trust, operational efficiency, and increased trade opportunities.

Regular quality assurance audits confirm that food safety procedures are implemented and maintained. Overbosch and Blanchard (2023) define quality assurance audits as methodical reviews of safety management systems that ensure compliance with best industry practices and regulatory requirements. Quality assurance audits support compliance with safety regulations, identify the potential for improvement and confirm the effectiveness of the solutions used (Rosak-Szyrocka and Abbase, 2020). While quality assurance audits are critical to food safety, Purwanto et al. (2020) note that they can be resource-intensive, disrupt operations, and lack transparency. Recognizing and mitigating these limitations ensures that audits drive continuous improvement and increase accountability for long-term success.

The goal of product recalls is to remove contaminated or unsafe products from the market, and efficient recall procedures minimize the impact of food safety incidents on public health and the organization's reputation (Dai et al., 2021). Gołaś (2020) point out that traceability systems are the backbone of effective recalls as they enable rapid identification and location of affected products. This is important in complex SCs, where products may pass through multiple intermediaries before reaching the consumer. According to Kravenkit and So-In (2022), companies can reduce the impact of security incidents and maintain consumer trust by emphasizing rapid identification, targeted searches, and efficient communication during recall scenarios. Product recalls and traceability systems are integral parts of effective food safety management, serving to protect public health, protect consumer trust, and protect the reputation of organizations in the food industry.

Insfran-Rivarola et al. (2020) indicate that employee training protects public health, meets regulatory standards, and maintains competitiveness in the food industry. According to Balwant (2020), training reduces risks, ensures compliance, improves food quality, reduces waste, and encourages a safety culture. It improves their skills, prepares them for emergencies, and promotes continuous development (Ma et al., 2020). Food safety and hygiene training improve the knowledge, attitudes and practices of food handlers. Mohammadi-Nasrabadi et al. (2021) agree that improving food handlers' knowledge, attitudes, and practices through training reduces the spread of diseases and thereby improves community health.

Maintaining public health, ensuring compliance with regulations and maintaining customer trust in the food sector all depend on the implementation of strict food safety guidelines and protocols. Adhering to standards such as HACCP, conducting regular quality assurance audits, implementing effective product recall procedures and providing thorough employee training are part of the multi-dimensional approach to food safety.

2.2. Supply chain performance

Maintaining competitive advantage, customer satisfaction and profitability depends largely on effective SC performance (Sharma et al., 2020). Hashmi (2022) argues that competitiveness and customer satisfaction depend on the efficient functioning of the SC and companies can significantly improve their SC operations by leveraging key performance measurements, implementing creative solutions, and removing obstacles. The use of artificial intelligence (AI) and machine learning for PA, blockchain for transparency, a growing focus on sustainability, and the use of advanced robotics and automation are some of the future trends in SC performance. These innovations will improve productivity, reduce human error, and increase transparency, thereby strengthening the security and reliability of SCs.

Kula et al. (2021) point out that the on-time performance ratio (OTD) is an organization's primary performance metric and helps identify issues related to project delivery and schedules, thereby facilitating system implementation. Additionally, Abdolazimi et al. (2020) emphasize that by comparing suppliers' performance to company standards, there is an opportunity to assess potential suppliers' quality and scheduling issues, which may lead to future purchases or even termination. If a company wants to maintain a high on-time delivery rate, it is crucial, it is critical to keep your team motivated, prevent burnout, and provide the necessary equipment and technology (Sheng Liu and Zuo-Jun, 2021).

Dias et al. (2022) informs that effective time management strategies and efficient plant and equipment operations are necessary to maintain focus and ensure on-time delivery, and this has a direct impact on customer satisfaction, performance measurement, competitive advantage, and operational efficiency. A company can increase SC efficiency, drive customer loyalty, and gain a competitive advantage in highly competitive industries by reliably meeting delivery deadlines (Helo and

Shamsuzzoha, 2020). Through the tracking of OTD rates, companies can identify and address inefficiencies. Optimizing delivery punctuality is an ongoing process that requires taking advantage of opportunities that arise and addressing obstacles head-on. Companies can differentiate themselves in the market, achieve exceptional operational performance, and increase consumer confidence by focusing on on-time deliveries. This effort to increase on-time delivery demonstrates a company's commitment to excellence. Any advance in this area has a significant impact, transforming tasks into extraordinary achievements.

High inventory turnover reflects efficient SC management that supports cost management, liquidity, demand forecasting and promoting better communication (Sheng Liu and Zuo-Jun, 2021). Increasing productivity, reducing costs, and streamlining the SC depend on inventory turnover ratios. Ali et al. (2022) proclaim that improving forecasts, optimizing inventory levels, strengthening supplier relationships, streamlining SC, managing product portfolios, and improving sales tactics are some of the strategies companies can implement to improve inventory turns. Strategies for managing the inventory turnover ratio include monitoring and adjusting inventory levels, improving product quality and relevance, inventory management techniques, and training and development (Alkahtani et al., 2021). These improve SC performance, reduce costs, and manage inventory more effectively. Demand forecasting, supplier connections, product portfolio management, sales tactics, and training are methods for success. Inventory turnover strategies face challenges such as complexity, regulatory concerns, and inaccurate forecasts. Companies should leverage just-in-time practices, analytics, supplier connections, optimized SCs, product portfolio management, and cross-functional teams. The inventory turnover ratio is a key figure for assessing and improving the efficiency of warehouse management in SC management. Companies can increase their operational efficiency, reduce costs, and better meet customer needs by continually evaluating and refining their ratio.

Customer satisfaction, loyalty, and overall operational efficiency are influenced by customer complaint resolution time and are therefore important performance metrics in SC management. Managing complaints leads to better customer relationships and competitive advantage. Complaint resolution positively impacts brand image by mitigating negative word of mouth (Assery et al., 2020). In modern businesses, social media and online reviews drive the impact of complaint resolution. Effective internal processes and technologies such as customer relationship management (CRM), employee development and training, communication channels, and efficient SC management influence conflict resolution. The use of technology, clearly defined protocols, and efficient procedures avoid delays, and well-trained staff can improve conflict resolution. A quick solution is also supported by unified communication systems and collaborations with suppliers and transport companies.

Tirkolaee et al. (2021) posit that AI and machine learning integrate feedback. Creating closed feedback systems shortens the time it takes to resolve complaints and has long-term benefits. Improved resolution times in SC performance lead to efficiency, customer retention, and revenue. Effective complaint handling promotes Customer Lifetime Value (CLV), quality standards and reduces the number of future complaints (Yilmaz et al., 2016). Efficiently managing customer complaint handling is critical to ensuring high customer satisfaction and operational efficiency.

Companies can reduce complaint resolution time by leveraging technology, improving processes, and addressing underlying issues. The benefits of faster complaint resolution include stronger customer loyalty, better business performance and competitive advantage, underscoring its importance as a priority in SC management.

2.3. Supply chain transparency

Supply Chain Transparency (SPT) is essential for modern food safety management and allows stakeholders to track and verify the journey of food from production to consumption (Otitolaiye and Abd Aziz, 2024). Montecchi et al. (2021) recognize that SC transparency improves traceability by providing detailed information about the origin, handling and movement of products in the event of a food safety incident. According to Karaosman and Barresi (2020), transparent SCs support risk management by identifying potential threats early and implementing preventive measures more effectively. Regulatory compliance and high food safety are also promoted through SC transparency. In addition, consumer confidence is strengthened and conscious food choices are made possible (Bratt and Sroufe, 2021).

Collaboration and accountability among all stakeholders are encouraged, leading to innovation and efficiency. Additionally, SC transparency supports ethical and sustainable practices in the food industry, ensuring food production meets ethical and sustainable goals. Measuring SC transparency requires assessing multiple criteria that indicate the level of information sharing and accessibility across the SC. These help to assess the transparency, accountability, and traceability of processes. Variables used to measure SC transparency include supplier transparency index, lead time variability, product traceability visibility, and customer feedback loop effectiveness.

The Supplier Transparency Index (STI) is a metric used to assess and measure the transparency that suppliers provide regarding their operations, sourcing practices and compliance with food safety standards (Apeji and Sunmola, 2022). From a different perspective, Moral-Pajares et al. (2020) value STI as a supplier transparency assessment tool based on precise standards and the measurement of the Supplier Transparency Index (STI). STIs are recorded through audits, third-party certifications and self-assessments. Suppliers receive reviews and are compared to competitors in the industry. Zheng et al. (2022) note that procurement. professionals use the STI as a tool to evaluate and select suppliers based on their commitment to transparency and the quality of the information they disclose. STI evaluates suppliers' transparency on source information, food safety standards, quality control, traceability systems, environmental and ethical practices, communication transparency, and compliance history and incidents. Through transparency, companies can ensure regulatory compliance, build trusted relationships with their suppliers, and meet customer demand for safe and responsibly sourced food. All parties involved in the SC benefit from the implementation of the STI, which also promotes an environment of transparency and accountability.

According to Dominguez et al. (2020), lead time variability is fluctuation in the time required to complete a SC process or activity. Variability impacts SC performance, inventory levels, and customer satisfaction in production, transportation, and delivery. Delivery networks should be reliable and efficient in detecting and controlling fluctuations in lead times. Equipment failures, supplier unreliability, weather, port congestion, customs clearance, customer demand, regulatory and compliance issues, and warehouse efficiency all contribute to fluctuations in turnaround times (Gupta et al., 2022). Lead time fluctuations result in higher inventory levels, customer service issues, SC costs, and more difficult production planning, potentially resulting in lost sales and revenue. Lund et al. (2020) highlight that the efficiency and reliability of the SC are significantly affected by delivery time fluctuations, and companies should reduce the impact of delivery time fluctuations. A comprehensive plan that incorporates supplier collaboration, control, transportation optimization, demand forecasting, process standardization, and the utilization of cutting-edge technology is necessary to efficiently manage the variations in lead times. SCs gain a competitive advantage in the market by reducing costs, increasing service standards, and improving overall resilience and responsiveness by reducing lead time variability.

The ability to track and trace an item's history, application, or location using documented identification is known as product traceability visibility (Schuitemaker and Xu, 2020). This allows stakeholders to keep track of items as they move through the SC, from raw materials to the final product delivered to customers. Patidar et al. (2021) postulate that food safety, quality control, regulatory compliance, and consumer trust are essential to product traceability. It also recognizes that product traceability visibility is a critical aspect that ensures food safety, increases SC efficiency, supports regulatory compliance, and builds consumer trust. Adopting consistent SC traceability frameworks and procedures ensures consistency and interoperability. Compliance and collaboration between SC participants are essential for successful traceability. Ultimately, better traceability leads to safer goods, more knowledgeable customers and a reliable SC.

Hazen et al. (2020) point out that customer feedback loops are crucial for collecting, analyzing, and acting on customer insights to improve products, services, and processes within the SC. Effective feedback loops enable companies to respond quickly to customer needs, increase customer satisfaction, and drive continuous improvement. Companies can achieve operational excellence, improve customer satisfaction, promote innovation, and improve product quality by systematically gathering, evaluating, and responding to consumer feedback (Shekarian, 2020). Companies should leverage a variety of channels, advanced analytics, segmentation, timely communication, proactive advertising, and CRM connectivity to improve the effectiveness of their customer feedback loops. Efficient customer feedback loops lead to more lasting competitive advantage in the market, increased customer loyalty, and stronger customer retention.

SC transparency is critical to maintaining food safety, building consumer trust and promoting ethical and sustainable business practices in the food sector. Transparency creates a more resilient and reliable food SC by encouraging innovation, strengthening traceability, strengthening risk management and ensuring regulatory compliance. Transparency not only protects public health but also ensures the sustainability and integrity of the global food system.

2.4. Technological integration

Seamlessly integrating multiple technologies into SC processes improves productivity, visibility, and responsiveness (Andarwati, 2018). While technology integration is noble, Lai (2017) complains that high acquisition costs, data security, interoperability issues, complexity, change management, reliability and maintenance are barriers to technological integration. Schniederjans et al. (2020) inform that Enterprise Resource Planning (ERP) systems, IoT, blockchain, AI, ML, advanced analytics, automation, robotics, cloud computing, and SC management software are examples of technologies that will be technologically integrated into SCs. These technologies improve SC efficiency, decision-making, data integrity, and coordination. When technology is integrated, the SC benefits from increased transparency, efficiency, agility, cost savings, risk management, and sustainability. It streamlines processes, reduces waste, and supports regulatory compliance through advanced analytics and blockchain.

According to Yang et al. (2021), the IoT market is expected to reach $ 1387.00 bn by 2024 and the market is expected to grow at a compound annual growth rate (CAGR) of 12.57% through 2024–2028. This increase is due to the growing demand for more efficient, automated, and real-time visible SC processes. The use of IoT devices in SC management is increasing with applications such as cold chain monitoring, warehouse management, transportation and logistics, and inventory management (Bui et al., 2021). Côrte-Real et al. (2020) also highlight that IoT devices support real-time inventory monitoring, route optimization, driver behavior monitoring, and tracking of items in transit. Drones and IoT-enabled cars are increasingly being used for inventory management, transportation, and packaging. Artificial intelligence (AI) and machine learning (ML) coupled with the Internet of Things (IoT) improve PA and decision-making capabilities, and promote innovation and efficiency in SC management.

Blockchain technology enables trustworthy and transparent commercial transactions without the need for an intermediatory governing body as it is built on a distributed, immutable digital record (Durach et al., 2021). Lohmer et al. (2022) pronounce that blockchain is a decentralized, immutable technology well suited to recording and confirming transactions in complex delivery networks. Wamba and Queiroz (2020) also argue that blockchain's immutable records ensure transparency, traceability, reduced fraud, efficiency, and cost savings. Blockchain technology is increasing in SCs as companies become aware of its potential for efficiency, transparency, and traceability. This technology will transform SC management by increasing productivity, reducing fraud, and promoting transparency.

PA Technologies are becoming increasingly important as companies seek to increase production, reduce costs and make better decisions. PA is a tool for identifying potential problems, predicting future trends, and improving SC operations by leveraging historical data, statistical algorithms, and machine-learning approaches According to Del Giudice et al. (2020), demand forecasting, inventory control, risk management in SC maintenance and reliability, freight optimization, and supplier performance analysis are all supported by PA. PA optimizes inventory, transportation routes, and maintenance schedules to ensure timely delivery and product availability, improving accuracy, efficiency, cost reduction, customer satisfaction, and competitive advantage (Del Giudice et al., 2020). However, Lee et al. (2022b) suggest that PA is associated with challenges, such as data quality, complexity, and high acquisition cost. The future of PA in SC management will include AI integration, real-time analytics, and increased IoT usage to improve accuracy and enable agile decision-making. Adopting PA tools is revolutionizing business operations by providing valuable insights, increasing productivity, and enabling proactive strategies. With technological advancements, the importance of PA in SC management is expected to increase, bringing significant benefits to companies that implement these innovative tools.

Investment in technology research and development (R&D) in SC management have increased as companies recognize the need to innovate and remain competitive (Parast, 2020). According to Liu et al. (2021), investments include new technologies such as artificial intelligence (AI), Internet of Things (IoT), blockchain, PA, robotics, and automation. These technologies increase efficiency, transparency, and resilience. Investments in technological research and development can improve SC operations' efficiency, reduce costs, increase agility, responsiveness, and sustainability, and improve visibility (Anser et al., 2020). The focus is on developing robust SCs, which has led to more money being invested in adaptive technologies. Investments in technology research and development stimulates creativity, increase productivity, and strengthen the overall robustness and flexibility of SCs, allowing companies to adapt to changing consumer needs and handle disruptions.

2.5. Predictive analytics as a mediating factor supply chain performance

Predictive analytics is transformative in improving SC performance by using data, statistical algorithms, and machine learning techniques to determine the likelihood of future outcomes based on historical data (Seyedan and Mafakheri, 2020). Moral-Pajares et al. (2020) point out that PA in SC management includes data collection and quality, statistical and machine learning models, model training, system integration, and user interface. This includes analyzing historical data, using statistical techniques, and providing easy-to-use dashboards for stakeholders to access predictive insights. According to Benzidia et al. (2021), improving demand forecasting, identifying seasonal trends, anticipating potential disruptions, enabling proactive mitigation, optimizing inventory management, reducing operational costs, and increasing customer satisfaction through on-time delivery and personalized experiences are benefits that of PA. The use of PA can impact SC performance in several dimensions e.g. on the accuracy of predictive models, the timeliness of risk warnings, cost savings through risk prevention, and stakeholder satisfaction.

Accuracy in predictive models refers to the precision and correctness of the predictions made by the model. In the context of SC management, accuracy determines the reliability of the predictions and insights derived from these models (Adedoyin et al., 2024). Accurate predictive models can effectively predict demand, optimize inventory, and predict potential disruptions. They assist with production planning by coordinating production schedules with expected demand, ensuring the effective use of production resources. Lee et al. (2022) highlight that predictive models improve operational efficiency by predicting equipment failures and minimizing downtime. Accurate predictions also assist in allocating resources effectively and ensure smooth production operations.

Predicting supplier performance and reliability contributes to intelligent procurement strategies and risk reduction, ensuring economical and uninterrupted operations (Lee et al., 2022). Accuracy and reliability of data, integration of diverse data sets, complexity management, and result interpretation are challenges faced by predictive models (McCarthy et al., 2022). Achieving precision requires careful data collection, consolidating information from multiple sources, and striking a balance between complexity and feasibility. Predictive model accuracy is a critical component that impacts supplier management, operational efficiency, and demand forecasting. Companies can use PA to optimize their SC operations, resulting in better decision-making, cost reduction, and improved overall performance. As PA technology advances, developing and maintaining accurate predictive models will be critical to staying ahead in SC management.

The speed at which SC stakeholders can be identified and informed of potential risks through predictive models is called timeliness. Essentially, it measures how quickly the system can detect anomalies and alert relevant parties. Timely risk warnings are essential in the fast-paced, dynamic world of SC management to minimize disruption. Munir et al. (2020) further indicate that timely notifications in SCs assist firms in reducing risks, ensuring uninterrupted operations, and executing backup plans. Yang et al. (2020) also postulate that they improve agility and responsiveness by enabling rapid responses to market fluctuations and disruptions. McGreevey et al. (2020) suggest that alarm fatigue is a significant barrier to risk management, as an overwhelming number of alarms can lead to desensitization and the risk that important alerts are missed. (McGreevey et al., 2020) also note that concerns about system compatibility and data integration can create challenges that can hinder the smooth flow of information and lead to delays in the generation of alerts.

An important component of SC management that can result in major cost savings is risk prevention. Through early detection and effective risk management, companies can avoid setbacks, maintain workflow effectiveness, and increase their overall revenue (McMaster et al., 2020). Al-Mhasnah et al. (2018) highlight that guaranteeing quality control and product recalls, ensuring sufficient insurance coverage, and shifting risks to other parties are viable options for risk evasion. Process efficiency and human error can be reduced by using technologies such as automation and artificial intelligence (AI), investing in energy-efficient technologies, and implementing sustainable principles. Implementing blockchain and IoT can also improve SC security and transparency and reduce the financial and operational impact of recalls. Cost savings through risk prevention avoid disruptions or inefficiencies in the SC through PA. These include direct savings, indirect savings, and investment returns that contribute to long-term financial health. It can be difficult to accurately quantify the cost savings achieved through proactive risk prevention. The initial cost of implementing PA can be high and requires clear proof of return on investment.

Stakeholder satisfaction with PA is critical to SC performance as it promotes trust, collaboration, and better decision-making (Sghir et al., 2023). High satisfaction levels encourage wider adoption and use, but barriers must be overcome, such as managing stakeholder expectations and effective communication (Freeman, 2023). Further to their assertion, Kumar and Ramachandran (2021) add that aligning SC strategies with overall business goals is critical for long-term planning. The accuracy and efficiency of SC ios increased through predictive insights, which also improves external and internal coordination and data sharing between manufacturing, logistics and procurement departments (Gray et al., 2022). Predictive insights increase operational efficiency through process optimization and correct resource allocation based on demand estimates and risk assessments. Sghir et al. (2023) also indicate that forecasting improves customer satisfaction and loyalty through timely fulfilment of requests. Proactively dealing with potential delays or problems ensures openness and trust with customers. Data openness and quality, acceptance resistance, education and training, system integration, and user-friendly interfaces are some of the challenges that PA must overcome

The challenges associated with implementing PA include maintaining consistency, overcoming data silos, managing complicated algorithms, maintaining models, ensuring compatibility with current systems, controlling implementation costs, gathering stakeholders and communicating the insights and benefits of PA. Future trends in PA for SC management include advanced machine learning and AI, big data analytics, real-time analytics, IoT sensor data, blockchain technology, collaborative platforms, and cross-industry data sharing. Deep learning algorithms improve prediction accuracy, AI integration improves decision-making, data lakes store and process massive amounts of data, IoT data improves predictive maintenance, and blockchain technology improves transparency and traceability. PA is a powerful tool that can significantly improve SC performance by improving demand forecasting, managing risk, optimizing costs, and increasing customer satisfaction. Despite the challenges related to data quality, model complexity, system integration, and stakeholder engagement, the benefits far outweigh the difficulties. As technology advances, the future of PA in SC management looks bright as continuous innovation and integration of advanced machine learning, AI, IoT, and blockchain technologies lead to even greater efficiency and effectiveness.

2.6. Study design and data analysis

The study model is based om (Attaran, 2020; Morgan et al., 2018; Maheshwari et al., 2020; Raspor, 2008; Sharma et al., 2020) to illustrate how PA influences food safety practice and procedure, SC transparency, technology integration and SC performance. The study develops a path model based on the empirical studies presented in **Figure 1**. Reflective constructs were created from reflective measurements measured on a single construct. The measurements used in the study were obtained using a five-point Likert scale questionnaire. As reported by Sarstedt et al. (2020), data collection and analysis included a pilot test of the questionnaire followed by online data collection among 426 Oman food industry. The sample size is sufficient to represent a population of one million participants as recommended by (Krejcie and Morgan, 1970). Participants included Oman food industry, Oman Logistics Association and the Middle East Logistics Industry members with 2–5 years of experience in the food industry. The participants were between 25 and 55 years old and had a minimum qualification of a university degree. Ethical approval was obtained from the Middle East College Centre for Research. Informed consent was obtained before data collection and the informed consent and confidentiality agreement were included on the coversheet of the questionnaire.

The conceptual model represents the interconnection of the Independent, mediating and dependent variables that provide the foundation for the study. The hypothesis states that food safety practices, supply chain transparency, and technological integration each have a direct impact on both predictive analytics and supply chain performance, with predictive analytics further mediating the relationship to improve supply chain performance. These variables are derived from the literature discussion help address the research gaps identified in the study. The data analysis process was systematic, as illustrated by (Hair et al., 2019; Joseph, 2024). The study evaluated the model's reliability, validity, and predictive accuracy, focusing on both manifest and latent variables.

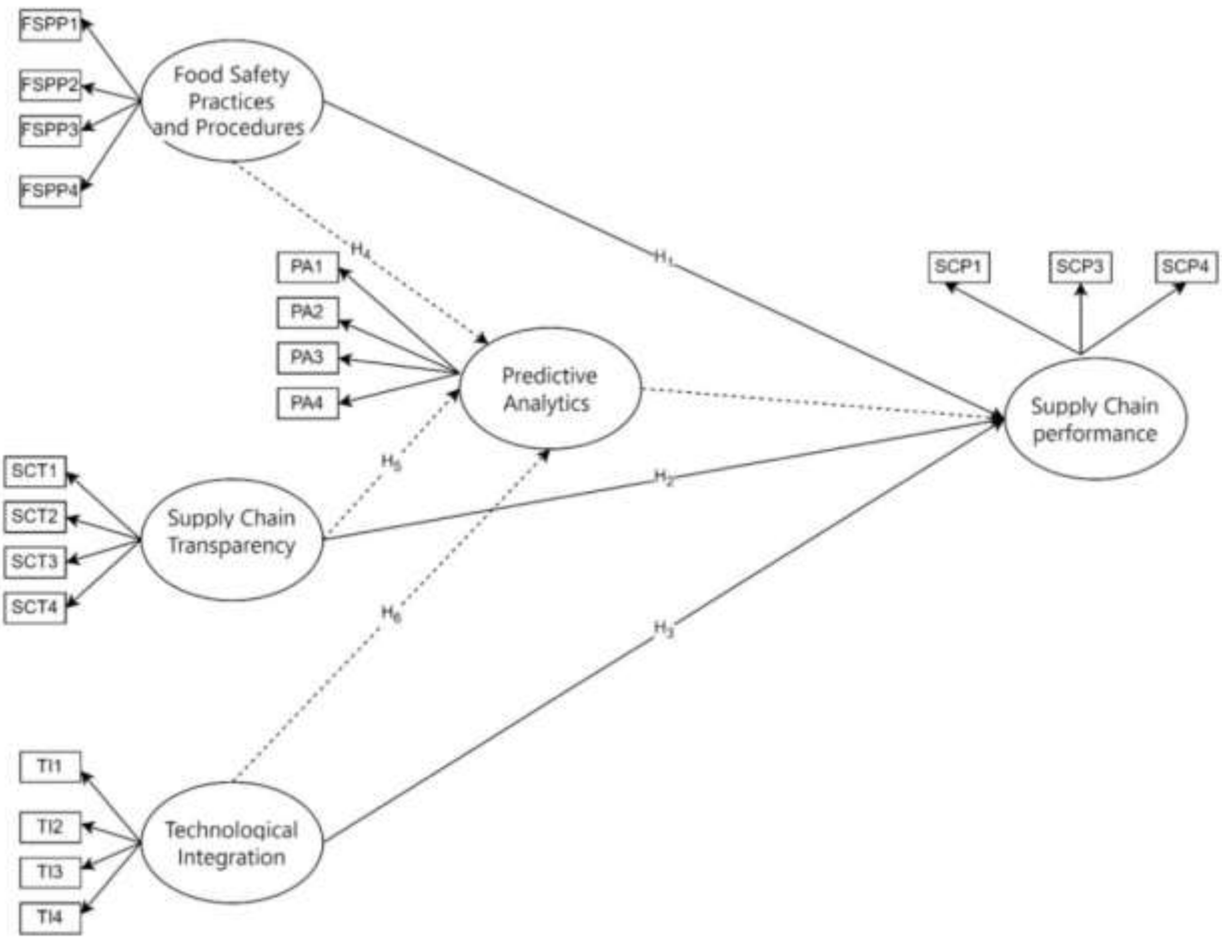

Figure 1. Conceptual model.

2.7. Assessment of measurement model

As suggested by Sarstedt et al. (2020), **Table 1** presents the evaluation of internal consistency reliability and convergent validity using the factor loading reliability test (Cronbach's alpha). The results in **Table 1** show that the model's reflectively measured construct is reliable and valid based on the rule of thumb. The factor loading is above the threshold of 0.7; the average variance is higher than 0.5, Cronbach's alpha shows excellent internal consistency above 0.8, and rho_a and rho_c show excellent reliability exceeding the threshold of 0.7. The study tested the discriminant validity of the model using the Heterotrait-monotrait ratio of correlation (HTMT). As described by Hair et al. (2019), all HTMT values show significant loading supporting the measures of discriminant validity. **Table 1**-Assessment of convergent validity and internal consistency reliability) and **Table 2**-Heterotrait-monotrait ratio of correlation (HTMT)) collectively confirm the construct used in the study has good convergent validity, making the model robust, credible and suitable for further analysis. The model shows that 59% of the variance of the dependent variable (SC performance)-R^2 is explained by the dependent variable (Food Safety Practice and Procedure, SC Transparency, and Technological Integration). Approximately 35.9% of the variance in another dependent variable is explained by the independent variables in the model. The higher and moderate R^2 values correlate with good predictive relevance of the model and strong explanatory power, supporting the continuation with PLS Predic (Franke and Sarstedt 2019).

Table 1. Assessment of convergent validity and internal consistency reliability.

Variables	Loading	Cronbach's alpha	(rho_a)	(rho_c)	(AVE)	R^2
FSPP-Food Safety Practice and Procedure		0.857	0.880	0.902	0.698	
	0.840					
	0.891					
	0.864					
	0.739					
PA-Predictive Analytics		0.912	0.918	0.939	0.794	0.59
	0.945					
	0.835					
	0.832					
	0.945					
SC Supply Chain Transparency		0.854	0.858	0.903	0.700	0.36
	0.908					
	0.908					
	0.773					
	0.744					
SC Supply Chain Performance		0.813	0.816	0.890	0.730	
	0.796					
	0.854					
	0.908					
TI-Technological Integration		0.883	0.893	0.918	0.738	
	0.829					
	0.890					
	0.890					
	0.823					

Table 2. Discriminant validity-Heterotrait-monotrait ratio (HTMT).

	Food Safety Practice and Procedure	PA	SC Transparency	SC Performance
FSPP-Food Safety Practice and Procedure				
PA-Predictive Analytics	0.323			
SC-Supply Chain Transparency	0.453	0.706		
SC-Supply Chain Performance	0.697	0.276	0.245	
TI-Technological Integration	0.233	0.806	0.673	0.140

3. Discussion of results

The study used statistical analysis tools such as convergent validity, Cronbach Alpha and composite reliability to validate and analyze the results. The assessment of whether multiple indicators of a construct use in a study converge or have a high proportion of variance is done using convergent validity. Internal consistency assesses the reliability of a construct by determining whether there is consistency in measuring the same concept within items selected for a construct. The traditional approach to the acceptable Cronbach Alpha value is that it should be greater than 0.70 for the results to be considered reliable (Roemer et al., 2021). The composite reliability value should be above 0.70 for the results to be considered good reliability, and values closer to 0.90 are considered much better.

H^1: Food safety practices and procedures influence the adoption of PA in the Oman food Industry.

The Values of factor loadings for items selected to measure how food safety practices and procedures influence the adoption of PA in Oman’s food industry range from 0.739 to 0.891, which is above the traditional threshold of 0.70, indicating a good convergence. The AVE value of 0.698 is above 0.50 of the recommended threshold, indicating that the construct captures significant variance. The path coefficient for FS and Procedure to PA is (0.072), t statistic = 1.719, p-value = 0.086 and VIF = 1.173 which does not reflect multicollinearity he results indicate that there is a weak relationship between the variables and a non-significant direct effect. The result suggests that food safety practices and procedures may impact the use of PA in Oman’s food industry, although this association may not have a positive impact.

H^2: Food safety practices and procedures influence the SC performance in the Oman Food Industry.

The Results of the data collected to measure the convergent validity of supply chain performance showed factor loadings between 0.796 and 0.908, indicating good convergent validity as these numbers are above the traditionally acceptable value of 0.70 From the results, an AVE value of 0.730 was obtained showing strong convergent validity. The results reflect a path coefficient (0.606) and a highly significant t-statistic = 11.960, as well as a p-value = 0.000 and VIF = 1.186, indicating no multicollinearity. The results indicate a strong and statistically significant effect, suggesting that food safety practices and procedures have a positive and strong impact on supply chain performance. These results shed light on the importance of understanding the relationship between food safety practices and procedures and SC performance. These results highlight the critical role of food safety in the overall efficiency and effectiveness of SC.

H[3]: PA adoption influences SC performance in the Oman Food Industry.

The data collected and calculated showed factor loading values between 0.832 and 0.945 indicating good convergence as they are above 0.70, the acceptable value. An AVE value of 0.794 was obtained demonstrating strong convergent validity. The results show a path coefficient of 0.189, t-statistic = 1.930, p-value = 0.054 and VIF = 2.469. These suggest a marginally significant positive relationship between predictive analysis and SC performance. Results suggest that supplier performance is moderately and positively influenced by predictive analytics. This implies that PA is important for improving SC performance. Therefore, the use of predictive analytics could lead to strategic decisions and performance improvements in the SC.

H[4]: SC transparency influences PA adoption in the Oman Food Industry.

The results show a path coefficient of 0.266, t-statistic = 4.144, p-value = 0.000 VIF = 1.728. this suggests that supply chain transparency has a positive and significant impact on predictive analysis. The results show that greater transparency and SC visibility promote the adoption of PA in the Oman food industry. The existence of transparent SC practices enables better collection and use of data, which provides a benchmark for predictive capabilities.

H[5]: SC transparency influences the adoption of PA in the Oman Food Industry.

The finding reflects a path coefficient of −0.032, t-statistic = 0.451, p-value = 0.652 and VIF = 1.903. The results show an unexpected negative and non-significant relationship. The results are not surprising, but highlight that online transparency may not lead to improvements in SC performance. This suggests that SC transparency needs to be supported by other factors to improve SC performance.

H[6]: Technological Integration influences the adoption of PA in the Oman food Industry.

The results of the data show factor loading values between 0.823 and 0.890, indicating good convergent validity as the values are above the prescribed value of 0.70. The AVE value of 0.738 is above the acceptable threshold of 0.50 threshold, indicating strong convergent validity. The results show a path coefficient of 0.559, t-statistics = 9.416, p-value = 0.000, VIF = 1.541. This reflects a strong and statistically significant positive relationship between technological integration and PA, suggesting that higher levels of technological integration have a positive impact on predictive analytics. This highlights the critical role of technological integration in driving PA adoption. The integration of technology in the SC is an important factor in the enhanced data collection, analysis and prediction capabilities of Industry 4.0, thereby improving the overall performance of the SC.

H[7]: Technology integration influences the SC performance of the Oman Food Industry.

The study shows a path coefficient of 0.003, t-statistics = 0.049, p-value = 0.961 VIF = 2.312. The relationship between technological integration and supply chain performance is negligible and statistically insignificant. The results suggest that technological integration does not directly enhance SC performance. This implies that technological integration is mediated by other variables, such as PA, rather than having a direct effect.

Based on the path coefficients and acceptable VIF that prove that there is low multicollinearity, robustness, and theoretical and practical relevance of the constructs the study will proceed to test the PLS prediction as recommended by (Shmueli et al., 2019). The model has demonstrated enough predictive accuracy that warrants further predictive analysis, which is critical in providing insightful, and practical conclusions to the study.

Additionally, PA shows consistently lower RMSE values as compared to LM, showing a better predictive accuracy while the SC performance indicators, LM show lower RMSE values, suggesting that LM predicts SC Performance outcomes better than PLS-SEM. Further to that, RMSE and MAE values are lower for PA indicators under PLS-SEM compared to LM, indicating better predictive accuracy for PA with PLS-SEM. For SCP indicators, LM shows lower MAE values, suggesting better predictive performance for SC Performance. As illustrated in **Table 3** Food Safety Practice and Procedure → SC Performance has a strong relationship (0.606, $p < 0.001$). These results are confirmed by the predictive accuracy (Q^2predict = 0.334) for SCP. These results confirm the model's predictive relevance for SCP to a moderate extent. **Table 3** reflects that Technological Integration → PA results of (0.559, $p < 0.001$) and SC Transparency → PA (0.266, $p < 0.001$). The results align with the high Q^2predict value (0.581) for PA, showing that these factors significantly contribute to the model's predictive power. In conclusion, the model PLS predict demonstrates high predictive relevance for PA (Q^2predict = 0.581) and moderate relevance for SC Performance (Q^2predict = 0.334).

The next section presents the PLS predict the assessment of the manifest variable (**Table 4**) and the PLS predict of the assessment of the Latent variable (**Table 5**). As suggested by Shmueli et al. (2019) the measurement model of constructs conforms to the relevant standards, allowing the study to proceed with smart PLS prediction. The measurement model has sufficient levels of reliability, convergent validity, discriminant validity, collinearity significance and relevance of the measurements (Hair et al., 2019; Shmueli et al., 2019). Using the rule of thumb, **Table 4** reflects the predictive performance of the model of. Partial Least Squares Structural equation modelling (PLS-SEM) approach with a traditional Linear Model (LM) using Q^2predict, RMSE (Root Mean Square Error), and MAE (Mean Absolute Error). The results are based on two subset variables PA and SC Performance. As suggested by Shmueli et al. (2019), Q^2predict measures predictive relevance with values > 0 indicating predictive relevance, and higher values suggest predictive accuracy, RMSE reflects the magnitude of prediction error, with values reflecting better predictive accuracy, MAE reflects the average absolute error of prediction, with lower values reflecting better predictive accuracy. **Table 4** shows that all values are > 0, hence illustrating that the model has good predictive relevance for all indicators. In this case, the predictive relevance is higher for PA indicators compared to SCP indicators, suggesting that the model predicts PA outcomes better than SC Performance outcomes. The results in **Table 5** indicate that Predictive Analytics has stronger predictive relevance (Q^2predict = 0.581) and better accuracy with lower errors (RMSE = 0.655, MAE = 0.494) compared to Supply Chain Performance (Q^2predict = 0.334, RMSE = 0.821, MAE = 0.629). Overall, the model is more reliable for predicting Predictive Analytics than Supply Chain Performance, which may require further refinement

Table 3. Assessment of structural model.

Constructs	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	*T* statistics (|O/STDEV|)	*P* values	VIF
Food Safety Practice and Procedure → PA	0.072	0.072	0.042	1.719	0.086	1.173
Food Safety Practice and Procedure → SC Performance	0.606	0.607	0.051	11.960	0.000	1.186
PA → SC Performance	0.189	0.192	0.098	1.930	0.054	2.469
SC Transparency → PA	0.266	0.270	0.064	4.144	0.000	1.728
SC Transparency → SC Performance	−0.032	−0.030	0.070	0.451	0.652	1.903
Technological Integration → PA	0.559	0.556	0.059	9.416	0.000	1.541
Technological Integration → SC Performance	0.003	0.001	0.066	0.049	0.961	2.312

Table 4. PLS predict the assessment of manifest variable.

	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
PA1	0.531	0.785	0.574	0.803	0.585
PA2	0.367	0.864	0.675	0.882	0.686
PA3	0.415	0.822	0.645	0.852	0.666
PA4	0.522	0.794	0.584	0.812	0.596
SCP1	0.217	1.316	1.109	1.177	0.905
SCP2	0.246	1.262	1.038	1.125	0.840
SCP3	0.269	1.273	1.027	1.134	0.852

Table 5. PLS predict LV summary.

Construct	RMSE	MAE
Predictive Analytics	0.655	0.494
Supply Chain Performance	0.821	0.629

4. Conclusion

Effective risk management is essential to maintain consumer trust, comply with legal obligations, ensure sustainable operations and gain a competitive advantage in the market. SC performance is the dependent variable examined, while PA is a mediating factor affecting this relationship. The study shows how SC managers' ability to anticipate and manage food safety threats can be significantly improved through PA. The study provides stakeholders with a roadmap to improve their food safety practices and maintain the integrity of their SCs. It provides actionable suggestions for the application of PA in food safety risk management. This study resulted in a comprehensive conceptual framework that can be used to improve risk management in the food safety supply chain through the use of predictive analytics. Furthermore, the conceptual framework emphasizes the importance for SC participants to collaborate and share information. For PA's success, manufacturers, processors, retailers and regulators must communicate and share data seamlessly. Openness and collaboration enable SCs to develop stronger and more coherent food safety risk management strategies. Overcoming obstacles such as data quality, data protection, and the need for specialized infrastructure and expertise requires constant study, technological investment and the creation of standardized protocols. The conceptual approach provides a tactical guide for integrating predictive analytics into food safety supply chain risk management. The framework can revolutionize traditional food safety protocols and lead to safer and more efficient SCs by using analytical tools and promoting collaborative efforts. The use of PA will be critical as the food industry evolves to protect health and well-being. This will ensure the safety of consumers and preserve the integrity of the global food supply.

The results highlight the transformative potential of predictive analytics to increase efficiency and cost-effectiveness, particularly for SMEs in highly competitive markets. Beyond the immediate operational benefits, predictive analytics aligns with global trends such as sustainability and supply chain transparency. Companies can reduce costs and promote environmental sustainability by minimizing waste and allocating resources as efficiently as possible. Additionally, predictive tools improve supply chain visibility, allowing companies to anticipate disruptions and improve decision-making, promoting transparency and trust between stakeholders. As companies increasingly adapt to these global demands, integrating predictive analytics will equip them not only to grow but also to adapt to evolving industry standards and customer expectations in a connected and sustainable economy. As concerns around supply chain resilience and sustainability grow, integrating predictive analytics not only addresses these challenges but also positions businesses to meet evolving industry demands and consumer expectations in a rapidly changing global market.

4.1. Recommendations

Companies should prioritize integrating various data sources such as IoT devices, sensor data, historical records, and external factors such as weather patterns and market trends to create comprehensive predictive models that accurately identify risk factors. The use of advanced machine learning and AI tools is essential for processing large data sets in real-time, enabling timely anomaly detection and trend forecasting. Through the development of scalable and affordable cloud-based solutions, forecasting tools become accessible to small and medium-sized businesses (SMBs) and extend the benefits across the entire supply chain. Collaborative data-sharing initiatives supported by secure blockchain technology can increase transparency and trust between stakeholders. Compliance with ethical and legal regulations must be a priority. Companies must ensure that data collection and analysis adhere to data protection standards and regulations in all jurisdictions. Training programs are critical to equip supply chain professionals with the skills to effectively use predictive analytics tools and interpret their results for proactive risk management. Pilot programs and case studies should be conducted to validate and refine predictive models so that practical adjustments can be made based on real-world feedback. Finally, forecasting systems must incorporate continuous improvement processes and regularly update data and algorithms to adapt to new risk factors and ensure ongoing model accuracy and relevance. Implementing these recommendations can promote a robust, data-driven approach to food safety that benefits all levels of the supply chain and protects consumer health.

4.2. Further research

Further research on using predictive analytics to improve food safety risk management in supply chains should target several key areas to refine and validate the conceptual framework. An important research direction is the development and testing of integrative models that combine machine learning, artificial intelligence (AI) and traditional statistical methods. This hybrid approach could improve the predictive capacity and reliability of food safety management systems in different supply chain segments. Future research should also address the scalability of these frameworks and focus on solutions that are accessible to smaller companies with limited resources. Longitudinal case studies and pilot projects are needed to validate predictive models in real-world conditions. Such empirical research can help identify practical challenges, validate conceptual assumptions, and refine the models based on field data. These efforts would help create adaptive and comprehensive frameworks that support proactive food safety risk management while maintaining supply chain efficiency and integrity.

Author contributions: Conceptualization, RM, CM and BR; methodology, RM, CM and BR; software, RM, CM and BR; validation, RM, CM and BR; formal analysis, RM, CM and BR; investigation, RM, CM and BR; resources, RM, CM and BR; data curation, RM, CM and BR; writing—original draft preparation, RM, CM and BR; writing—review and editing, RM, CM and BR; visualization, RM, CM and BR; supervision, RM, CM and BR; project administration, RM, CM and BR; funding acquisition, RM, CM and BR. All authors have read and agreed to the published version of the manuscript.

Conflict of interest: The authors declare no conflict of interest.

References

Abdolazimi, O., Salehi Esfandarani, M., Salehi, M., & Shishebori, D. (2020). Robust design of a multi-objective closed-loop supply chain by integrating on-time delivery, cost, and environmental aspects, case study of a Tire Factory. Journal of Cleaner Production, 264, 121566. https://doi.org/10.1016/J.JCLEPRO.2020.121566

Adedoyin Tolulope Oyewole, Chinwe Chinazo Okoye, Onyeka Chrisanctus Ofodile, & Emuesiri Ejairu. (2024). Reviewing predictive analytics in supply chain management: Applications and benefits. World Journal of Advanced Research and Reviews, 21(3), 568–574. https://doi.org/10.30574/wjarr.2024.21.3.0673

Ali, K., Showkat, N., & Chisti, K. A. (2022). Impact of Inventory Management on Operating Profits: Evidence from India. Journal of Economics, Management and Trade, 28(9), 22–26. https://doi.org/10.9734/jemt/2022/v28i930435

Alkahtani, M., Omair, M., Khalid, Q. S., Hussain, G., Ahmad, I., & Pruncu, C. (2021). A covid-19 supply chain management strategy based on variable production under uncertain environment conditions. International Journal of Environmental Research and Public Health, 18(4), 1–23. https://doi.org/10.3390/ijerph18041662

Al-Mhasnah, A. M., Salleh, F., Afthanorhan, A., & Ghazali, P. L. (2018). The relationship between services quality and customer satisfaction among Jordanian healthcare sector. Management Science Letters, 8(12), 1413–1420. https://doi.org/10.5267/j.msl.2018.10.003

Andarwati, M. (2018). Analysis of Factors Affecting the Successof Accounting Information Systems Based on Information Technology on SME Managementsas Accounting InformationEnd User. 98.

Anisatul, A., & Handoko, F. N. (2020). The Application of Haccp (Hazard Analysis Critical Control Point) in Food Production Department. Jurnal Sosial Humaniora Terapan, 2(2). https://doi.org/10.7454/jsht.v2i2.84

Anser, M. K., Khan, M. A., Awan, U., Batool, R., Zaman, K., Imran, M., Sasmoko, Indrianti, Y., Khan, A., & Bakar, Z. A. (2020). The role of technological innovation in a dynamic model of the environmental supply chain curve: Evidence from a panel of 102 countries. Processes, 8(9). https://doi.org/10.3390/pr8091033

Apeji, U. D., & Sunmola, F. T. (2022). ScienceDirect ScienceDirect Principles and Factors Influencing Visibility in Sustainable Supply Principles and Factors Influencing Visibility in Sustainable Supply Chains Chains. Procedia Computer Science, 200, 1516–1527. https://doi.org/10.1016/j.procs.2022.01.353

Assery, S., Tjahjono, H. K., Palupi, M., & Dzakiyullah, N. R. (2020). The role of conflict resolution on supply chain performance. International Journal of Scientific and Technology Research, 9(3), 4007–4011.

Balwant, P. T. (2020). Training and Development of Instructor-Leadership : An Instructional Systems Design Approach. Journal of Human Services: Training, Research, and Practice Volume, 6(1).

Belhadi, A., Kamble, S. S., Venkatesh, M., Chiappetta Jabbour, C. J., & Benkhati, I. (2022). Building supply chain resilience and efficiency through additive manufacturing: An ambidextrous perspective on the dynamic capability view. International Journal of Production Economics, 249, 108516. https://doi.org/10.1016/J.IJPE.2022.108516

Benzidia, S., Makaoui, N., & Bentahar, O. (2021). The impact of big data analytics and artificial intelligence on green supply chain process integration and hospital environmental performance. Technological Forecasting and Social Change, 165, 120557. https://doi.org/10.1016/J.TECHFORE.2020.120557

Bratt, C., & Sroufe, R. (2021). Implementing Strategic Sustainable Supply Chain Management.

Brun, A., Karaosman, H., & Barresi, T. (2020). Supply chain collaboration for transparency. Sustainability (Switzerland), 12(11). https://doi.org/10.3390/su12114429

Bui, T. D., Tsai, F. M., Tseng, M. L., Tan, R. R., Yu, K. D. S., & Lim, M. K. (2021). Sustainable supply chain management towards disruption and organizational ambidexterity: A data driven analysis. Sustainable Production and Consumption, 26, 373–410. https://doi.org/10.1016/J.SPC.2020.09.017

Côrte-Real, N., Ruivo, P., & Oliveira, T. (2020). Leveraging internet of things and big data analytics initiatives in European and American firms: Is data quality a way to extract business value? Information & Management, 57(1), 103141. https://doi.org/10.1016/J.IM.2019.01.003

Dai, B., Nu, Y., Xie, X., & Li, J. (2021). Interactions of traceability and reliability optimization in a competitive supply chain with product recall. European Journal of Operational Research, 290(1), 116–131. https://doi.org/10.1016/J.EJOR.2020.08.003

De Boeck, E., Jacxsens, L., Kurban, S., & Wallace, C. A. (2020). Evaluation of a simplified approach in food safety management systems in the retail sector: A case study of butcheries in Flanders, Belgium and Lancashire, UK. Food Control, 108. https://doi.org/10.1016/j.foodcont.2019.106844

Del Giudice, M., Chierici, R., Mazzucchelli, A., & Fiano, F. (2020). Supply chain management in the era of circular economy: the moderating effect of big data. International Journal of Logistics Management, 32(2), 337–356. https://doi.org/10.1108/IJLM-03-2020-0119

Dias, E. G., de Oliveira, L. K., & Isler, C. A. (2022). Assessing the effects of delivery attributes on e-shopping consumer behaviour. Sustainability (Switzerland), 14(1), 1–19. https://doi.org/10.3390/su14010013

Dominguez, R., Cannella, S., Ponte, B., & Framinan, J. M. (2020). On the dynamics of closed-loop supply chains under remanufacturing lead time variability. Omega, 97, 102106. https://doi.org/10.1016/J.OMEGA.2019.102106

Durach, C. F., Blesik, T., von Düring, M., & Bick, M. (2021). Blockchain Applications in Supply Chain Transactions. Journal of Business Logistics, 42(1), 7–24. https://doi.org/10.1111/jbl.12238

Franke, G., & Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: a comparison of four procedures. Internet Research, 29(3), 430–447. https://doi.org/10.1108/INTR-12-2017-0515/FULL/XML

Gołaś, Z. (2020). The effect of inventory management on profitability: Evidence from the Polish food industry: Case study. Agricultural Economics (Czech Republic), 66(5), 234–242. https://doi.org/10.17221/370/2019-AGRICECON

Gray, G., Cooke, G., Murnion, P., Rooney, P., & O'Rourke, K. C. (2022). Stakeholders' insights on learning analytics: Perspectives of students and staff. Computers & Education, 187, 104550. https://doi.org/10.1016/J.COMPEDU.2022.104550

Gupta, P., Hurburgh, C. R., Bowers, E. L., & Mosher, G. A. (2022). Application of fault tree analysis: Failure mode and effect analysis to evaluate critical factors influencing non-GM segregation in the US grain and feed supply chain. Cereal and Grains Association, 99(6), 1394–1413. https://doi.org/10.1002/cche.10601

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203/FULL/XML

Hashmi, A. (2022). Factors Affecting the Supply Chain Resilience and Supply Chain Performance. South Asian Journal of Operations and Logistics, 1(2), 53–73. https://doi.org/10.57044/sajol.2022.1.2.2212

Hazen, B. T., Russo, I., Confente, I., & Pellathy, D. (2020). Supply chain management for circular economy: conceptual framework and research agenda. International Journal of Logistics Management, 32(2), 510–537. https://doi.org/10.1108/IJLM-12-2019-0332

Helo, P., & Shamsuzzoha, A. H. M. (2020). Real-time supply chain—A blockchain architecture for project deliveries. Robotics and Computer-Integrated Manufacturing, 63, 101909. https://doi.org/10.1016/J.RCIM.2019.101909

Ibrahim, O. O. (2020). Introduction to Hazard Analysis and Critical Control Points (HACCP). EC Microbiology, 4, 93–99.

Insfran-Rivarola, A., Tlapa, D., Limon-Romero, J., Baez-Lopez, Y., Miranda-Ackerman, M., Arredondo-Soto, K., & Ontiveros, S. (2020). A systematic review and meta-analysis of the effects of food safety and hygiene training on food handlers. Foods, 9(9). https://doi.org/10.3390/foods9091169

Joseph, H. M. S. C. R. S. G. (2024). Advanced Issues in Partial Least Squares Structural Equation Modeling. Sage Publication Inc.

Kamboj, S., Gupta, N., Bandral, J. D., Gandotra, G., & Anjum, N. (2020). Food safety and hygiene: A review. International Journal of Chemical Studies, 8(2), 358–368. https://doi.org/10.22271/chemi.2020.v8.i2f.8794

Kondaveeti, H. K., Simhadri, C. G., Yasaswini, G. L., & Shanthi, G. K. (2023). The use of artificial intelligence in the food industry: From recipe generation to quality control. Impactful Technologies Transforming the Food Industry, 116–134. https://doi.org/10.4018/978-1-6684-9094-5.CH008

Kravenkit, S., & So-In, C. (2022). Blockchain-Based Traceability System for Product Recall. IEEE Access, 10(September), 95132–95150. https://doi.org/10.1109/ACCESS.2022.3204750

Krejcie, R., & Morgan, D. W. (1970). Determining Sample Size for Research Activities. Educational and Psychological Measurement, 30, 607-610. http://www.sciepub.com/reference/145556

Kudashkina, K., Corradini, M. G., Thirunathan, P., Yada, R. Y., & Fraser, E. D. G. (2022). Artificial Intelligence technology in food safety: A behavioral approach. Trends in Food Science & Technology, 123, 376–381. https://doi.org/10.1016/J.TIFS.2022.03.021

Kula, E., Greuter, E., Van Deursen, A., & Georgios, G. (2021). Factors Affecting On-Time Delivery in Large-Scale Agile Software Development. IEEE Transactions on Software Engineering, 48(9), 3573–3592. https://doi.org/10.1109/TSE.2021.3101192

Kumar, V., & Ramachandran, D. (2021). Developing firms’ growth approaches as a multidimensional decision to enhance key stakeholders’ wellbeing. International Journal of Research in Marketing, 38(2), 402–424. https://doi.org/10.1016/J.IJRESMAR.2020.09.004

Lai, P. C. (2017). THE LITERATURE REVIEW OF TECHNOLOGY ADOPTION MODELS AND THEORIES FOR THE NOVELTY TECHNOLOGY. Journal of Information Systems and Technology Management, 14(1), 21–38. https://doi.org/10.4301/S1807-17752017000100002

Lee, C. S., Cheang, P. Y. S., & Moslehpour, M. (2022). Predictive Analytics in Business Analytics: Decision Tree. Advances in Decision Sciences, 26(1), 1–29. https://doi.org/10.47654/V26Y2022I1P1-30

Lee, K. L., Romzi, P. N., Hanaysha, J. R., Alzoubi, H. M., & Alshurideh, M. (2022). Investigating the impact of benefits and challenges of IOT adoption on supply chain performance and organizational performance: An empirical study in Malaysia. Uncertain Supply Chain Management, 10(2), 537–550. https://doi.org/10.5267/j.uscm.2021.11.009

Liu, H., Fan, L., & Shao, Z. (2021). Threshold effects of energy consumption, technological innovation, and supply chain management on enterprise performance in China’s manufacturing industry. Journal of Environmental Management, 300, 113687. https://doi.org/10.1016/J.JENVMAN.2021.113687

Lohmer, J., da Silva, E. R., & Lasch, R. (2022). Blockchain Technology in Operations & Supply Chain Management: A Content Analysis. Sustainability (Switzerland), 14(10), 1–88. https://doi.org/10.3390/su14106192

Lund, S.; Manyika, J.; Woetzel, J.; Bsrriball, Ed.; Krishnan, M.; Alicke, K.; Birshan, M.; George, K., Smit, S.; Swan, D.; Hultzler, K. (2020). and Rebalancing in Global Value Chains. In McKinsey Global Institute (Issue August).

Ma, X., Nakab, A., & Vidart, D. (2020). Human Capital Investment and Development: The Role of On-the-job Training.

Masengu, R., Al Habsi, J. S., Ruzive, B., Muchenje, C., & Tsikada, C. (2024). Food Traceability Technology and Compliance Measures in Fast Food Retails: The Mediating Effect of Supply Chain Efficiency on Consumer Trust. Studies in Systems, Decision and Control, 545, 563–576. https://doi.org/10.1007/978-3-031-65203-5_50

Masengu, R., Mohamed, E. D., Benson, R., & Jouhara, A. H. (2024). Effectiveness of food quality and safety management systems in Oman's food supply chain. https://doi.org/10.21203/RS.3.RS-3867358/V1

McCarthy, R. V., McCarthy, M. M., & Ceccucci, W. (2022). Applying Predictive Analytics. Applying Predictive Analytics. https://doi.org/10.1007/978-3-030-83070-0

McGreevey, J. D., Mallozzi, C. P., Perkins, R. M., Shelov, E., & Schreiber, R. (2020). Reducing Alert Burden in Electronic Health Records: State of the Art Recommendations from Four Health Systems. Applied Clinical Informatics, 11(1), 1–12. https://doi.org/10.1055/s-0039-3402715

McMaster, M., Nettleton, C., Tom, C., Xu, B., Cao, C., & Qiao, P. (2020). Risk Management: Rethinking Fashion Supply Chain Management for Multinational Corporations in Light of the COVID-19 Outbreak. Journal of Risk and Financial Management, 13(8). https://doi.org/10.3390/jrfm13080173

Mohammadi-Nasrabadi, F., Salmani, Y., & Esfarjani, F. (2021). A quasi-experimental study on the effect of health and food safety training intervention on restaurant food handlers during the COVID-19 pandemic. Food Science and Nutrition, 9(7), 3655–3663. https://doi.org/10.1002/fsn3.2326

Montecchi, M., Plangger, K., & West, D. C. (2021). Supply chain transparency: A bibliometric review and research agenda. International Journal of Production Economics, 238, 108152. https://doi.org/10.1016/J.IJPE.2021.108152

Moral-Pajares, E., Martínez-Alcalá, C., Gallego-Valero, L., & Caviedes-Conde, Á. A. (2020a). Transparency index of the supplying countries' institutions and tree cover loss: Determining factors of EU timber imports? Forests, 11(9), 1–16. https://doi.org/10.3390/F11091009

Moral-Pajares, E., Martínez-Alcalá, C., Gallego-Valero, L., & Caviedes-Conde, Á. A. (2020b). Transparency index of the supplying countries' institutions and tree cover loss: Determining factors of EU timber imports? Forests, 11(9), 1–16. https://doi.org/10.3390/F11091009

Munir, M., Jajja, M. S. S., Chatha, K. A., & Farooq, S. (2020). Supply chain risk management and operational performance: The enabling role of supply chain integration. International Journal of Production Economics, 227, 107667. https://doi.org/10.1016/J.IJPE.2020.107667

Otitolaiye, V. O., & Abd Aziz, F. S. (2024). Bibliometric analysis of safety management system research (2001–2021). Journal of Safety Research, 88, 111–124. https://doi.org/10.1016/j.jsr.2023.10.014

Overbosch, P., & Blanchard, S. (2023). Principles and Systems for Quality and Food Safety Management. Food Safety Management: A Practical Guide for the Food Industry, Second Edition, 497–512. https://doi.org/10.1016/B978-0-12-820013-1.00018-8

Parast, M. M. (2020). The impact of R&D investment on mitigating supply chain disruptions: Empirical evidence from U.S. firms. International Journal of Production Economics, 227, 107671. https://doi.org/10.1016/J.IJPE.2020.107671

Patidar, A., Sharma, M., & Agrawal, R. (2021). Prioritizing drivers to creating traceability in the food supply chain. Procedia CIRP, 98, 690–695. https://doi.org/10.1016/J.PROCIR.2021.01.176

Purwanto, A., Sulistiyadi, A., Primahendra, R., Kotamena, F., Prameswari, M., & Ong, F. (2020). Does quality, safety, environment and food safety management system influence business performance? Answers from indonesian packaging industries. International Journal of Control and Automation, 13(1), 22–35.

Raspor, P. (2008). Total food chain safety: how good practices can contribute? Trends in Food Science & Technology, 19(8), 405–412. https://doi.org/10.1016/J.TIFS.2007.08.009

Rincon-Ballesteros, L., Lannelongue, G., & González-Benito, J. (2024). Cross-Continental Insights: Comparing Food Safety Management Systems In Europe And Latin America. Food Control, 110552. https://doi.org/10.1016/j.foodcont.2024.110552

Roemer, E., Schuberth, F., & Henseler, J. (2021). HTMT2–an improved criterion for assessing discriminant validity in structural equation modeling. Industrial Management and Data Systems, 121(12), 2637–2650. https://doi.org/10.1108/IMDS-02-2021-0082

Rosak-Szyrocka, J., & Abbase, A. A. (2020). Quality management and safety of food in HACCP system aspect. Production Engineering Archives, 26(2), 50–53. https://doi.org/10.30657/pea.2020.26.11

Sarstedt, M., Hair, J. F., Nitzl, C., Ringle, C. M., & Howard, M. C. (2020). Beyond a tandem analysis of SEM and PROCESS: Use of PLS-SEM for mediation analyses! International Journal of Market Research, 62(3), 288–299. https://doi.org/10.1177/1470785320915686/ASSET/IMAGES/LARGE/10.1177_1470785320915686-FIG2.JPEG

Schniederjans, D. G., Curado, C., & Khalajhedayati, M. (2020). Supply chain digitisation trends: An integration of knowledge management. International Journal of Production Economics, 220, 107439. https://doi.org/10.1016/J.IJPE.2019.07.012

Schuitemaker, R., & Xu, X. (2020). Product traceability in manufacturing: A technical review. Procedia CIRP, 93, 700–705. https://doi.org/10.1016/J.PROCIR.2020.04.078

Seyedan, M., & Mafakheri, F. (2020). Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities. Journal of Big Data, 7(1). https://doi.org/10.1186/s40537-020-00329-2

Sghir, N., Adadi, A., & Lahmer, M. (2023). Recent advances in Predictive Learning Analytics: A decade systematic review (2012–2022). In Education and Information Technologies (Vol. 28, Issue 7). Springer US. https://doi.org/10.1007/s10639-022-11536-0

Sharma, R., Kamble, S. S., Gunasekaran, A., Kumar, V., & Kumar, A. (2020). A systematic literature review on machine learning applications for sustainable agriculture supply chain performance. Computers & Operations Research, 119, 104926. https://doi.org/10.1016/J.COR.2020.104926

Shekarian, E. (2020). A review of factors affecting closed-loop supply chain models. Journal of Cleaner Production, 253, 119823. https://doi.org/10.1016/J.JCLEPRO.2019.119823

Sheng Liu, L. H., & Zuo-Jun, M. S. (2021). On-Time Last-Mile Delivery : Order Assignment with On-Time Last-Mile Delivery : Order Assignment with. Management Science, 67(7), 4095–4119.

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. European Journal of Marketing, 53(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189/FULL/PDF

Tirkolaee, E. B., Sadeghi, S., Mooseloo, F. M., Vandchali, H. R., & Aeini, S. (2021). Application of Machine Learning in Supply Chain Management: A Comprehensive Overview of the Main Areas. Mathematical Problems in Engineering, 2021(Ml). https://doi.org/10.1155/2021/1476043

Wamba, S. F., & Queiroz, M. M. (2020). Blockchain in the operations and supply chain management: Benefits, challenges and future research opportunities. International Journal of Information Management, 52, 102064. https://doi.org/10.1016/J.IJINFOMGT.2019.102064

WHO. (2022). Food safety. World Helath Organisation. https://www.who.int/news-room/fact-sheets/detail/food-safety

Yang, M., Fu, M., & Zhang, Z. (2021). The adoption of digital technologies in supply chains: Drivers, process and impact. Technological Forecasting and Social Change, 169, 120795. https://doi.org/10.1016/J.TECHFORE.2021.120795

Yilmaz, C., Varnali, K., & Kasnakoglu, B. T. (2016). How do firms benefit from customer complaints? Journal of Business Research, 69(2), 944–955. https://doi.org/10.1016/J.JBUSRES.2015.08.038

Zheng, M., Li, Y., Su, Z., Fan, Y. Van, Jiang, P., Varbanov, P. S., & Klemeš, J. J. (2022). Supplier evaluation and management considering greener production in manufacturing industry. Journal of Cleaner Production, 342, 130964. https://doi.org/10.1016/J.JCLEPRO.2022.130964