OPERATIONS AND SUPPLY CHAIN MANAGEMENT
Special Issue on AI, Cyber-Physical Systems, and Decision Making in OSCM
Vol. 18, No. 2, 2025, pp. 300 – 317 , ISSN 1979 – 3561 | EISSN 2579 - 9363

AI in Supply Chain: Techniques, Applications, Real-World Cases and Benefits under SCOR Framework

Hoang Bao Pham
Department of Industrial Engineering and Information Systems, Faculty of Management and Economics, Tomas Bata University in Zlin, Czech Republic.
Email: pham_hoang@utb.cz (Corresponding)

Petr Bris
Department of Industrial Engineering and Information Systems, Faculty of Management and Economics, Tomas Bata University in Zlin, Czech Republic.
Email: bris@utb.cz

ABSTRACT

This article focuses on practical perspectives of Artificial Intelligence (AI) applications in Supply Chain Management by exploring commonly used AI techniques, use cases and benefits of applying AI in Supply Chain Management with real-world examples from multinational corporations like DHL, IBM, Walmart, Amazon, Google, among others. The findings are grouped according to the four stages of the SCOR (Supply Chain Operations Reference) framework, i.e plan, source, make, deliver, to facilitate visualization. We find that AI techniques including Neural Networks, Genetic Algorithms, Support Vector Machines, Reinforcement Learning, Fuzzy Logic, and Natural Language Processing are applied to enhance supply chain efficiencies, lower costs, increase profits, improve customer satisfaction, save operational time, reduce potential disruption, better suppliers/customers relationships, improve product quality, enhance safety, and shorten lead times... These stem from nine benefit groups, namely PLAN (demand forecasting, inventory optimization, supply risk mitigation), SOURCE (procurement, supplier selection), MAKE (product quality assurance, smart warehouse management, predictive maintenance), DELIVER (route optimization, dynamic pricing, and last mile delivery, and customer service). Limitations and future research directions are discussed.

Keywords: ***artificial intelligence (AI); machine learning (ML); supply chain management (SCM); logistics; applications; use cases; industry examples, SCOR***

1. INTRODUCTION

The world is becoming increasingly interconnected and compact, while the global supply chain (SC) is growing progressively intricate. As an example, Apple relies on 43 suppliers scattered across 6 continents to assemble and manufacture its iconic iPhone. Even a seemingly simple product like a tennis ball travels through 11 countries across 4 continents during its manufacturing process (Petrova, 2018; Carrington, 2016). Moreover, in light of emerging global challenges such as the COVID-19 pandemic, political tensions, and unforeseen weather events, Supply Chain Management (SCM) has become riskier than before. Adding to the complexity, there is now an unprecedented surge in the generation of SC-related data. It is now believed that at least from 2.5 quintillion bytes of big data is being generated every day. To illustrate, let's consider a simple case from the automotive industry where the number of potential solutions in SCM is remarkably high, exceeding 12 million in typical scenarios and reaching 4.8×10^{18} in complex cases (Mourtzis and Doukas, 2015). Such vast possibilities necessitate the adoption of an intelligent system to effectively handle such infinite potentials. This is where AI (Artificial Intelligence) comes into the picture. According to McKinsey's 2018 report titled "Notes from the AI frontier: Insights from hundreds of use cases," AI has the potential to generate up to US$5.8 trillion in value across 9 business functions, with SCM being one of the sectors that stands to benefit the most (McKinsey, 2018b).

So far many systematic literature reviews, general overview articles or bibliography articles on the topic of AI application in SCM have been conducted (Riahi *et al.,* 2021; Tirkolaee *et al.,* 2021; Richey *et al.,* 2023; Aamer *et al.,* 2021; Sandra and Bernd, 2021; Min, 2010; Pournader *et al.,* 2021; Riahi *et al.,* 2021; Toorajipour *et al.,* 2021; Shavaki & Ghahnavieh, 2023; Raza *et al.,* 2023…) but they mainly deal with the technical or theoretical perspectives and do not elaborate on specific industry examples or did so in a limited way while papers on AI practical applications in SCM are mainly from corporate consultancies, company or expert blogs, and sporadic newspaper articles (DHL, 2018; DHL, 2019; McKinsey, 2017; McKinsey, 2018a; McKinsey, 2018b; Deepika, 2023; Patyane, 2023; Boualam, 2023…). Hence, there lacks a comprehensive scholarly article that addresses both

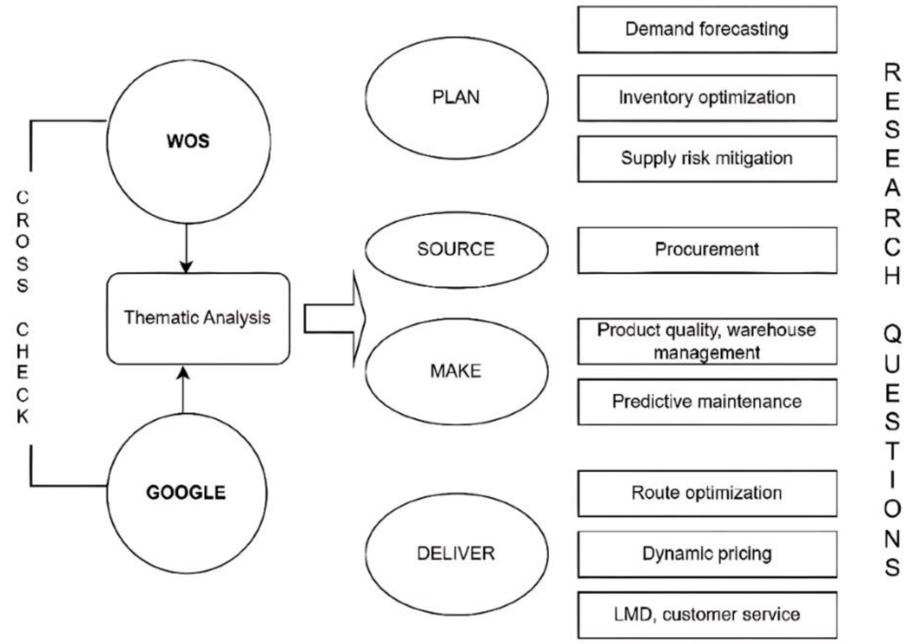

Figure 1 Summary of research steps.

theoretical and practical aspects, with a specific emphasis on industry applications. This is the first such article as far as we know. To enhance visualization, the theoretical and practical benefits are grouped into 4 main SC stages according to the SCOR (Supply Chain Operations Reference) framework: i.e. plan, source, make, deliver as established by the Supply Chain Council now merged with the Association for Supply Chain Management. This framework is the first and the most widely accepted cross-industry standard for SCM (Stewart, 1997; Ren *et al.,* 2006). Incorporating the SCOR model to categorize benefits provides a structured and comprehensive framework for analysis. SCOR's standardized process categories offer a systematic lens through which AI-driven improvements can be clearly mapped and evaluated. Beyond enhancing visualization, SCOR's process-oriented structure enables researchers to systematically align AI applications with specific supply chain functions for better organization of findings and improving comparability across studies.

While previous reviews have often focused either on theoretical AI techniques or isolated case studies, this paper bridges that gap by integrating both perspectives within a unified SCOR-based framework. By doing so, it uncovers patterns of AI adoption across various supply chain functions and showcases the real-world value of AI applications in different industry contexts. This dual focus allows for a more holistic understanding of how AI tools are being used in practice, offering insights into their practical implications, scalability, and sector-specific nuances. This is the first study to combine theoretical insights with practical use cases, presenting specific AI methods, real-world industry applications, and their associated benefits, all mapped to the SCOR model. It not only classifies AI techniques and generic use cases but also highlights how these tools are implemented by multinational corporations and startups alike.

This work advances the academic understanding of AI in supply chain management by offering a structured classification of AI methods, use cases, and benefits. It enriches the theoretical landscape by connecting AI capabilities directly to supply chain outcomes within the SCOR framework. For practitioners and managers, this paper provides actionable insights into the potential of AI in specific industry settings. Through detailed examples from diverse companies, it serves as a valuable guide for those considering adopting AI technologies, helping them better understand the tangible benefits and real-world implications of implementation.

2. RESEARCH METHODS

This is an overview paper based on information from corporate white papers, newspapers and scholarly articles. Contents are extracted from two main search frameworks: Google and WOS (Web of Science) platforms. We conducted an initial search by typing the keywords [IN TITLE] ("Artificial Intelligence" OR "AI" OR "Machine Learning" OR "ML") AND ("supply chain" OR "logistics" OR "SCM") AND [IN ABSTRACT] ("use cases" OR "examples" OR "applications") on WOS – filtered for articles only in English and in the last 5 years. 82 scholarly papers were found, most of which paid scant attention to specific use cases and industry examples or failed to mention them at all.

We later did a similar search plus "-scholar" and "filetype:pdf" on Google.com to exclude scholarly articles to obtain a comprehensive overview of practical examples sourced from company websites, blogs, white papers, and industry publications of multinational corporations (MNCs) such as DHL, IBM, as well as consulting firms like McKinsey, among others. Since we want practical industry examples and consultations, corporate white papers, which pertain to gray literature, a Google search is appropriate for this purpose (Juricek, 2009; Piasecki *et al.,* 2018). To ensure the validity and reliability of the data, we cross-referenced the information with mainstream media sources via Google News. Guidelines or white papers from big MNCs are preferred over small corporate communiques or private blogs. We also used Google Scholar for broader coverage.

Based on our preliminary findings, we proceeded to categorize these findings based on similarities in their use cases. For systematic organization, we grouped them into the four SCOR stages with nine associated themes, namely PLAN (demand forecasting, inventory optimization, supply risk mitigation), SOURCE (procurement, supplier selection), MAKE (product quality assurance, smart warehouse management, predictive maintenance), DELIVER (route optimization, dynamic pricing, and last mile delivery, and customer service), aiming to address the following four research questions (RQ):

RQ1: To overview AI techniques across four SCOR stages
RQ2: To identify AI use cases across four SCOR stages
RQ3: To identify industry examples that apply AI in SCM
RQ4: To identify benefits of AI in SCM in four SCOR stages

The remainder of this paper is structured as follows: Section 3 reviews AI and supply chain management. Section 4 presents AI use cases categorized under the four SCOR stages, along with associated techniques and real-world examples and tangible benefits. Section 5 offers a summary discussion of key findings, limitations and outlines future research directions. Section 6 concludes the study, followed by a list of abbreviations and references.

3. AI, SCM AND SCOR

Artificial Intelligence (AI) is broadly defined as a system capable of emulating human cognition and performing adaptive actions in real-world environments. Machine Learning (ML), a subset of AI, encompasses the algorithms and techniques that allow these systems to detect patterns, make decisions, and improve performance through continuous analysis of diverse input data (Sun *et al.,* 2024). Meanwhile, there are various definitions of SCM provided by respected global organizations such as the Council of Supply Chain Management Professionals, the Global Supply Chain Forum, APICS – the Association for Operations Management, the Chartered Institute of Purchasing & Supply, and the Logistics & Supply Chain Management Society. While these definitions may vary in their perspectives and emphasis, most converge on the idea that SCM involves the integrated management of the flow of goods, services, and information across the entire supply chain network—from raw material suppliers to end customers (Felea *et al*., 2013).

According to the SCOR model developed by the Supply Chain Council now merged with the Association for Supply Chain Management, SCM is divided into four stages: PLAN, SOURCE, MAKE, and DELIVER (Ntabe *et al.,* 2015). There is also a RETURN stage (Ntabe *et al.,* 2015) but since we consider "return" the reverse of the earlier 4 stages, we will not consider it in this article. This SCOR is a widely recognized framework and is the first and most widely accepted cross-industry standard for SCM (Stewart, 1997; Ren *et al.,* 2006) and has been extensively studied in relation to AI applications in SCM: Babai *et al.,* (2025), Derfoufi & Benrrezzouq (2024), Harrir & Sari (2024), Ehrenthal *et al.,* (2024), Chehbi-Gamoura *et al.,* (2019), Khan *et al.,* (2023), Mendonça & Lima (2023), Cannas *et al.,* (2023), Kamble *et al.,* (2023), Lima-Junior & Carpinetti (2019).

Incorporating the SCOR model to categorize benefits provides a structured and comprehensive framework for analysis. SCOR's standardized process categories offer a systematic lens through which AI-driven improvements can be clearly mapped and evaluated. Beyond enhancing visualization, SCOR's process-oriented structure enables researchers to systematically align AI applications with specific supply chain functions, facilitating better organization of findings and improving comparability across studies. This approach simplifies the evaluation of how various AI techniques are applied and their impacts within each process area, thereby increasing the discussion's relevance for both academic research and industry practice. In this way, it not only strengthens the analytical rigor of the article but also enhances its practical value for SC professionals to understand and implement AI solutions.

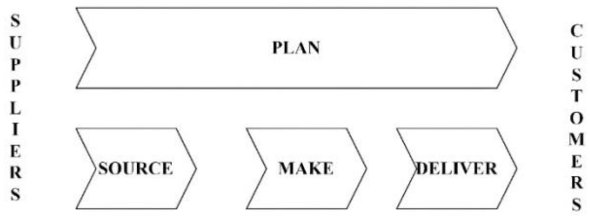

Figure 2 Four major SC stages

4. RESEARCH FINDINGS

This section presents the findings structured around nine key themes or use cases aligned with the four SCOR stages. Each theme corresponds to a major AI use case in supply chain management, derived from nine benefit groups: PLAN (demand forecasting, inventory optimization, supply risk mitigation), SOURCE (procurement and supplier selection), MAKE (product quality assurance, smart warehouse management, predictive maintenance), and DELIVER (route optimization, dynamic pricing, last-mile delivery, and customer service). For each group, the section discusses relevant AI techniques, practical use cases, industry examples, and the associated benefits.

4.1 Plan

4.1.1 Demand Forecasting

Demand forecasting or demand planning holds paramount importance in SCM as it serves as a foundation for various other SC processes, including procurement, inventory planning, manufacturing, and distribution planning. In their comprehensive literature review on AI/ML techniques for demand planning in SCM from 2005 to 2019, Seyedan & Mafakheri (2020) found that the most commonly used method is NN (Neural Networks), appearing in 30 articles, followed by regression with 27 articles. Time-series forecasting using ARIMA (Autoregressive Integrated Moving Average) was mentioned in 13 articles, while both SVM (Support Vector Machines) and Decision Tree methods were cited in 8 articles each. Similarly, Carbonneau *et al.* (2008) conducted a study on ML in SC demand planning and identified RNN (Recurrent Neural Networks) as the best predictor model. Following RNN, SVM, NN, and Multiple Linear Regression were also found to be effective predictor models for demand planning in SCM.

The significance of predictive planning became evident in 2017 when fidget spinners, a small toy that gained unexpected popularity, became a best-seller, selling a reported 50 million units within a few months. This sudden surge in demand caused shipment stagnation and supply chain delays, with the toys accounting for 17% of all retail toy sales in the US in May, 2017 (Dundas, 2018). The craze was fueled by viral videos of teenagers playing with fidget spinners. By leveraging AI and mining social media posts, blogs, and YouTube videos, predictive analytics could have anticipated this boom, accurately projected the demand for the toys, and consequently prevented shipment delays and extended lead times.

According to Hitachi Insight Group's Vice President, Greg Kinsey, AI predictive analytics has the potential to enhance SC efficiencies by 10% (Arsene, 2022). McKinsey (2018a) also suggested that ML can reduce forecasting errors by 20% to 50%. Lingam (2018) demonstrated how AI-driven demand forecasting models improved accuracy by 20%, leading to lower inventory costs and improved customer satisfaction. In 2015, an industry report by MHI said that the adoption level of predictive analytics in SCM was at 25%. However, it was projected to soar to 77% within the following six years (MHI, 2015), underlining the growing recognition of the value of predictive planning in optimizing SC operations.

Various variables, such as price, discounts, promotions, seasonal factors, entertainment or political events, weather forecasts, past sales track records, and text mining through social media reviews and ecommerce sites using NLP (Natural Language Processing), as well as real-time data from shipments, traffic conditions, media news, and mobile phones, can all be harnessed to predict product demand accurately. Unsupervised learning can be employed to train machines with unlabeled data, allowing them to identify unexpected patterns, such as detecting previously unseen delays in transportation times with novel causes.

An exemplary case is observed in the German e-retailer Otto, which utilizes ML and deep learning to analyze a vast dataset of 3 billion transactions and approximately 200 variables, including weather, historical sales, and web searches. Based solely on AI recommendations, without human supervisors' involvement, Otto purchases around 200,000 items monthly to proactively prepare for future demand and maintain a high level of delivery efficiency. This approach liberates human managers from the decision-making process, enabling them to focus on more strategic issues. It is worth noting that Otto's AI-driven demand forecast for a specific month is reported to be up to 90% accurate (The Economist, 2017; Wolfgang, 2021).

Also in Germany, the drugstore chain DM (Drogerie Markt) harnesses the power of AI to anticipate weekly demand by utilizing input variables, such as SKU (Stock Keeping Unit)-level data, over a span of 6 months. By using a training dataset from the past 2.5 years, DM achieves highly accurate demand forecasts, leading to cost reductions and increased customer satisfaction (Wenzel *et al.,* 2019). In 2016, Nike from the United States faced a dip in profits due to faulty demand prediction. Learning from this experience, the sportswear giant later acquired Celect, an AI data predictive analytics firm, three years later (Thomas, 2019). Meanwhile, Accenture collaborated with General Electric on TALERIS, a predictive analytics tool tailored for smart service operations in the airline industry.

Predictive analytics has advanced to the extent that AI can forecast a customer's potential purchase of a specific product even before they have made any order. In 2012, US ecommerce giant Amazon introduced the concept of anticipatory delivery and even filed a patent for this approach in August that year. It was approved in December of the following year. Utilizing customer data, such as search history, purchase history, and shopping cart contents, Amazon anticipated when a customer would buy a particular product and shipped it to them before they even placed the order (Lomas, 2014). Amazon also efficiently calculated the destination hub for a group of future buyers near their addresses using complex algorithms, enabling seamless and anticipatory delivery. American logistics company UPS (United Parcel Service) has also successfully implemented ML for demand forecasting during holiday peaks and last-minute demand spikes.

ML is also utilized to predict ship destination arrival times using data from GPS and AIS (Automatic Identification System), where ships continuously transmit data on their speed, location, route, and weather conditions. By integrating weather and speed data through ML algorithms, the arrival times of ships can be predicted effectively, even in cases where precise location information is unavailable. California-based telecom maker Infinera employs Intrigo Systems to predict delivery dates of components using ML. By analyzing past logistics provider performance and production lead times, Infinera gains valuable insights into delivery schedules (Korolov, 2018). This reduction in lead times translates to improved customer satisfaction and financial gains. Furthermore, precise demand forecasts also facilitate lean inventory management. With better predictions of customer demand, companies can optimize inventory levels, reduce excess stock, and minimize costs associated with holding inventory, which leads to another AI applicability: inventory optimization.

4.1.2 Inventory Optimization

Inventory optimization or stock level optimization is the process of determining the optimal inventory levels to strike a balance between localized and centralized storage. Overreliance on centralized inventorying poses risks of stockouts, while excessive localized storage can be costly. Since the annual holding stocks cost might take up to 35% of a product value (Timme and Williams-Timme, 2003), inventory optimization could serve as a very effective way to substantially lower costs.

Marr (2017) highlighted that AI-driven inventory optimization models take into account factors such as demand variability, lead times, and supply chain constraints. to avoid both overstocking and understocking, businesses track sales and store inventory in real-time. In this domain, GA (Genetic Algorithms) and ANN (Artificial Neural Networks) are commonly suggested to effectively manage inventory levels (Paul and Azeem, 2011; Sandra and Bernd, 2021; Praveen *et al.,* 2019). Priore *et al.* (2019) adopted ML, specifically inductive learning to determine the best inventory replenishment policy, achieving an accuracy rate of 88% and reducing operation costs. Sharma and Singh (2021) also applied ML, specifically Random Forest and XGBoost, to predict demand and achieve optimum stock levels in what they call "intelligent warehouse stocking".

RL (Reinforcement Learning) also plays a crucial role in this process, as it allows AI systems to learn and prescribe the optimal amount of stocks to be kept at any given time. By leveraging trial and error, AI can minimize inventory holding costs while preventing stockout costs. Through AI-enabled prescriptions, businesses can make informed decisions on when, what, and how much to order from suppliers, optimizing inventory management and minimizing waste and carbon footprints. This approach aligns with the principles of Just-In-Time (JIT), ensuring efficient and sustainable inventory practices.

By integrating various factors such as economic trends, potential pandemic outbreaks, and material prices into an AI-powered system, instant and real-time inventory decisions can be prescribed, enabling efficient stock placement and sales management. This approach replaces manual ordering methods, ensuring accurate and timely inventory management within the ERP (Enterprise Resource Planning) system. This ensures that only necessary items are stocked, minimizing waste, and allows for the proactive ordering of soon-to-be popular products, as predicted by AI. Constantly monitoring demand volatility, while maintaining delivery readiness, drives down the inventory-to-sales ratio, a pivotal metric in effective stock management. Furthermore, AI's adaptability allows for the creation of up-to-the-minute online promotions based on demand, leading to reduced inventory levels and further optimizing SC operations.

According to McKinsey (2018a), ML can reduce lost sales from stockouts by up to 65% and inventory reductions of 20 to 50%. For example, Microsoft successfully reduced its inventory by a significant US$200 million by leveraging AI and IoT (Internet of Things) capabilities. Lennox was able to cut data collection time by an impressive 90%, while the Komplett group managed to increase SC efficiency by nearly 30% (Ozdogru, 2020).

In the UK, the National Grid employs Google's DeepMind technology to anticipate the optimal level of demand versus supply, considering various input variables such as weather conditions and other relevant factors (Yao, 2018). Additionally, the AI system implemented by German e-retailer Otto has proved highly beneficial and led to a remarkable 20% reduction in surplus inventory and significantly decreased product returns by over 2 million items per year (The Economist, 2017; Wolfgang, 2021). In the same vein, Walmart uses AI-based demand forecasting algorithms to adjust inventory levels based on changing customer preferences and market dynamics. This allows the retail giant to optimize inventory levels, reduce excess inventory and improve shelf availability. Companies like Nike also leverage AI to predict upcoming styles and fashion trends, better preparing them for future inventory supply to meet customer demands effectively.

AI-driven inventory management becomes even more crucial when handling perishables due to the intricate interplay of multiple variables. These variables, including expiry dates, product age, temperature, humidity levels, and the conditions of transporting containers and storage shelves, can significantly impact the quality and shelf life of perishable goods. AI can precisely track the expiration dates of each perishable product, ensuring timely removal of items nearing their end of life. Furthermore, it can optimize storage conditions by adjusting temperature and humidity levels, thereby preserving the freshness and overall quality of the perishables. AI-powered algorithms can also predict demand patterns for perishable items based on historical data, weather conditions, and seasonal trends. This enables businesses to proactively manage their inventory levels, minimizing waste and ensuring adequate stock availability during peak demand periods. Moreover, it can provide early warnings of spoilage or quality deterioration, allowing businesses to take prompt action, such as expedited deliveries or targeted promotions, to mitigate any impacts.

4.1.3 Supply Risk Mitigation

AI proves to be a valuable tool in effectively minimizing various supply risks, such as bottlenecks, bullwhip effects, calamities, and other potential disruptions. Predicting the estimated arrival time of shipments becomes crucial for companies to notify customers and loaders in advance or adjust cross-docking operations as needed. In scenarios where shipments may be held overnight at customs due to bureaucracy or missing documents, AI's predictive abilities become vital in avoiding potential delays that could incur significant costs in JIT mismatches. AI can proactively suggest solutions in real-time to minimize these supply risks.

Various AI techniques applied in this domain include ANN/SVM which is used to quantify various resilient strategies for risk mitigation (Rajesh, 2020), and FL (Fuzzy Logic) to reduce the bullwhip effect as proposed by Balan *et al.* (2007). Mogre *et al.* (2016) suggested a DSS (Decision Support System) using Decision Trees to prescribe SC risk mitigation and strategies when the risks materialize.

Watson, an AI-enabled tool developed by US giant chipmaker IBM, is equipped with the capability to track social media trends, predicting potential occurrences like political riots, work strikes, financial climate, and weather patterns. This analytical prowess allows Watson to effectively monitor SC risks and offer solutions ranked by priority, helping businesses make informed decisions and mitigate potential disruptions. Additionally, IBM's AI-powered Supply Chain Insights further aids clients in streamlining their decision-making processes by reducing risks and disruptions in SC operations.

Germany-headquartered logistics giant DHL (Dalsey Hillblom Lynn) has developed AI-powered Resilience360, a cloud-based supply chain risk mitigation platform, that utilizes ML and NLP to analyze unstructured texts from over 300,000 online sources and sentiments from a staggering 8 million posts. This powerful tool serves as an early warning system for potential SC risks, providing

Table 1 Summary of AI techniques, use cases, examples and proven benefits in the PLAN stage

Use Cases (RQ2)	AI Techniques (RQ1)	Industry Examples (RQ3)	Beneficial Results (RQ4))
Demand Forecasting	RNN, SVM, NN	Otto, DM, Nike, Accenture & General Electric (TALERIS), Amazon, UPS…	Enhance SC efficiencies by 10% Reduce forecasting errors by 20% to 50% 90% accuracy in demand forecast (Otto) Anticipatory delivery (Amazon) Lower inventory costs, Increase profits, Improve customer satisfaction
Inventory Optimization	ANN, GA, RL, Random Forest	Nike, Microsoft, Lennox, UK's National Grid (Google's DeepMind), Otto, Walmart	Reduce lost sales from stockouts by 65% Cut inventory by 20 to 50%. Reduce inventory by $200 million (Microsoft) 20% reduction in surplus inventory (Otto) Decrease product returns by over 2 million items per year (Otto) JIT practices, Less time consuming, Better meet customer demand
Supply Risk Mitigation	ANN, SVM, FL, Decision Trees, NLP	IBM (Watson), DHL (Resilience360), Microsoft & Apple & Ford Motor (Flex Pulse), Johnson & Johnson	Analyze over 300,000 online sources from 8 million posts to warn potential SC risks (Resilience360) Predict daily transit time 7 days in advance & forecast delays (DHL) Lower potential threats, Reduce otherwise huge costs, Reduce potential SC disruption delays

valuable insights to mitigate disruptions effectively (DHL, 2018).

Utilizing ML, DHL leverages predictive capabilities to forecast delays in air freight transit with remarkable precision. By accurately predicting the average daily transit time for a particular lane seven days in advance, DHL enables proactive planning for freight forwarders, streamlining logistics operations and ensuring timely deliveries (DHL, 2018). Another notable AI solution in the industry is US-based Flex's AI software, Flex Pulse, which excels in predicting SC risks such as work strikes, calamities, and other potential disruptions. With an impressive clientele including Microsoft, Apple, and Ford Motor, Flex Pulse significantly contributes to enhancing risk management strategies. During the COVID-19 pandemic, companies like US pharmaceutical firm Johnson & Johnson too used AI-driven analytics to assess and mitigate SC disruptions.

ML also plays an important role in predicting the occurrence of delays and expected arrival times of components during transit. If crucial components face delays, alternative routes, re-routing, or emergency shipments can be suggested to minimize disruptions and maintain efficient operations. Moreover, AI can predict food spoilage by monitoring the specific temperature and time requirements for each food product. Unexpected delays or force majeure events affecting temperature can be accounted for, allowing for proactive measures to prevent spoilage.

4.2 Source

4.2.1 Procurement, supplier selection

AI offers significant advantages in the realm of procurement and supplier selection. One of its key benefits is the ability to efficiently identify the most optimal suppliers and cost-effective options. Through comprehensive analysis of suppliers' risk profiles, track records, and feedback, AI assists in evaluating and ranking potential suppliers and transporters. With the help of an AI-driven DSS, businesses can streamline their supplier evaluation process, automating the ranking of suppliers based on various parameters and criteria. This data-driven approach ensures that the procurement team can make well-informed decisions, selecting suppliers who offer the best value, reliability, and quality.

Procurement systems using AI can automate tasks such as purchase requisition, supplier negotiation, and contract management to streamline the purchasing process. Sharma *et al.,* (2022) found that the most popular AI techniques in selecting suppliers are a combination of fuzzy set theory and MCDM (Multicriteria Decision-Making) models. Other systems include ANN and genetic algorithms (Riahi *et al.,* 2021) while other scholars combined ANN with additional approaches like Data Envelopment Analysis (DEA) and Analytic Network Process (ANP) for supplier selection (Kuo *et al.,* 2010).

Table 2 Summary of AI techniques, use cases, examples and proven benefits in the SOURCE stage

Use Cases (RQ2)	AI Techniques (RQ1)	Industry Examples (RQ3)	Beneficial Results (RQ4))
Procurement, Supplier Selection	FL, ANN, GA, Decision Trees, SVM, Q learning, NLP	Scoutbee, SAP Ariba, Toyota, Walmart (Pactum AI)	Close deals with suppliers in days instead of months (Walmart) Cost savings, Risk management, better supplier partnerships, less time consuming, increased profits

Besides ANN, other ML techniques most commonly used in supplier selection are Decision Trees and SVM and Q learning (Tirkolaee *et al.,* 2021.) FL (Fuzzy Logic) is also suggested for supplier selection (Carrera and Mayorga, 2008) for new product development.

In terms of procurement, AI contract management solutions like Conga Contracts automate the creation, review, and monitoring of contracts. These systems use AI to extract key terms, analyze clauses and ensure compliance (Hirvonen-Ere, 2023). Contract management automation accelerates the procurement process and reduces contract risks. In terms of documentation, Coupa, an AI-powered expense management platform, uses NLP to process purchase orders and invoices automatically (Kumar *et al.,* 2023). This reduces manual effort and minimizes errors.

For supplier selection, Scoutbee from Germany developed an AI-powered system to help companies find the best suppliers globally by analyzing vast amounts of data from a variety of sources. It collects and processes data from various suppliers, including their capabilities, track records, certifications, financial stability, and customer feedback and uses NLP to interpret and understand unstructured data, such as supplier profiles, news articles, and social media posts, to gain deeper insights into potential suppliers. In 2020 Scoutbee raised $60 million in Series B funding to expand the system (Musgrove, 2020).

Other examples include AI-driven procurement systems such as SAP Ariba that use ML algorithms to automatically identify and evaluate potential suppliers based on historical data, performance metrics, and market intelligence (Yarramalli, 2020; Singh, 2023). Leavy (2023) highlighted how AI improves supplier relationship management by analyzing historical data and assessing risks. Organizations such as Japanese carmaker Toyota have implemented AI-driven supplier assessment systems to identify potential SC risks and disruptions. These systems facilitate informed supplier selection, negotiation, and risk mitigation decisions. AI collaboration platforms have changed the way SC partners communicate and coordinate.

In 2023, Bloomberg highlighted that Walmart has used chatbots for negotiating optimal pricing and payment terms with several suppliers and vendors through Pactum AI's chatbot. This intelligent system has the capability to analyze present supplier proposals against historical data and competitor pricing. With the assistance of AI chatbots, deals that once took weeks or even months when solely handled by humans are now closed within days, ultimately bolstering profitability.

4.3 Make

4.3.1 Product Quality Assurance and Smart Warehouse Management

In manufacturing, image recognition powered by Machine Vision plays a vital role in identifying and sorting products, detecting defects, scratches, or dents. Cameras equipped with AI can also conduct product counts and promptly alert human operators in case of missing items or potential thefts. Machine Vision is powered by several AI techniques including CNN (Convolutional Neural Network), Object Recognition, Image Segmentation, among others.

Such image processing techniques are employed to detect surface imperfections like dents and scratches on products. This level of precision is particularly valuable to industries like car makers. Sensor data, including radar sensors and Lidar (Light Detection and Ranging), enables AI to distinguish between moving and static objects and classify them based on Semantic Segmentation, localization, and Instance Segmentation. Additionally, RFID (Radio Frequency Identification) technology is widely used for product tracking and identification.

Zhao *et al.,* 2021 used CNN to successfully identify nearly 98% of defects in the textile industry. Similarly, Unajan *et al.,* (2019) applied Machine Vision with Deep Learning to accurately identify product scraps with an accuracy rate of 85% while Villalba *et al.,* (2019) developed DNN (Deep Neural Network) to successfully and automatically classify 98.4% of products in the production of gravure cylinders. In warehouses, AI-driven programs monitor employee movements, allowing for accurate predictions of task completion times. IBM's Watson, for instance, demonstrates exceptional accuracy in detecting cargo defects from real-time images, achieving over 90% accuracy (Binns, 2018). Detected anomalies are relayed to maintenance teams for timely correction. Watson, fed with images from cameras installed along the tracks, will classify and identify damages and prescribe suitable repairs for wagons (DHL, 2018).

Companies like GreyOrange utilize AI warehouse services to handle changing inventories and demand volatilities in real-time, reducing lead times, and ultimately improving customer satisfaction and order fulfillment. In the field of robotics, Deep Learning has brought about a transformation by empowering robots to manipulate objects without reliance on fixed positions. Finnish firm ZenRobotics utilizes ML and Machine Vision in its robot system to identify different labels and logos on beverage and food cartons, as well as recyclables. The robots efficiently sort and pick up these items from conveyor belts at an impressive rate of 4,000 items per hour. (DHL, 2018). UK supermarket Ocado utilizes AI-enabled robots to transport products to human workers responsible for packing them into shopping bags for delivery (Dale, 2018). Subsequently, other robots or cobots (collaborative robots) carry the bags to trucks driven by humans, destined for customers' homes. According to McKinsey (2017), such cobots can increase productivity by an impressive 20%.

Similarly, German retailer Metro Cash & Carry leverages ML to differentiate between stationary and moving pallets on RFID-tagged loading ramps, significantly reducing false positive readings and correctly classifying over 95.5% of data (Wenzel *et al.,* 2019). Japanese firm NEC utilizes image recognition technology to efficiently sort products and determine which items to ship, matching a scheduled list (Yosuke *et al.,* 2017). Meanwhile, US chipmaker Intel Corp employs ML to expedite the resolution of design problems for semiconductor makers, increasing efficiency in the manufacturing process (Burgess, 2018).

Advancements in speech-to-text technology have given rise to voice-powered AI, constantly improving accuracy. It is estimated that humans misunderstand an average of 6% of words, while AI-enabled voice assistants equipped with state-of-the-art speech-to-text technology can reduce this error rate to even less than 5%, surpassing human language comprehension (Yakubovskyi and Morozov, 2023). Voice recognition technology powered by Deep Learning guides operators on what and where to pick orders, while truck drivers can communicate with their trucks to identify the destination terminal using earplugs.

To ensure the well-being of employees in these smart warehouses 4.0, IoT (Internet of Things) wearables are provided to the operators. These wearables can capture and monitor abnormal data, such as heart rate, blood pressure, or falls. If any anomalies are detected, the supervisors are immediately alerted, allowing prompt assistance. Additionally, the conditions of stock are constantly monitored using heat and humidity sensors, ensuring the proper storage of products. RFID technology is employed to trace incoming and outgoing inventory, enabling efficient tracking and management. All collected data is seamlessly integrated into an ERP system for comprehensive analysis and decision-making.

Moreover, RFID technology has been adopted by various companies, including Walmart, Procter & Gamble, and the US Department of Defense, for tracking products and preventing theft. RFID readers and tags record essential data like ID numbers, product types, and manufacturer names, facilitating efficient inventory management. Beyond product tracking, warehouse management programs can also utilize data to track the movement of employees, enabling the prediction of task completion times and enhancing overall operational efficiency. Canadian startup TwentyBN has developed an AI technology capable of analyzing human behavior through video feeds, enabling it to detect incidents such as people falling or engaging in shoplifting activities. This application enhances operational safety and helps prevent accidents and thefts in various settings. In 2021, it was acquired by US mobile tech firm Qualcomm (Freeman, 2021).

Other examples of smart warehousing come from the Chinese e-commerce giant Alibaba, which operates a warehouse in Huiyan. In this warehouse, 60 robots are employed to transport items weighing up to half a ton to human workers responsible for packing. These robots are equipped with laser sensors that enable them to scan their surroundings, avoiding collisions with objects and personnel. Additionally, they autonomously navigate to charging stations when required. This efficient system increases stock handling capacity by up to three times while reducing labor costs by an impressive 70% (Alim & Kesen, 2020).

Sohrabi (2023) discussed how AI-enabled IoT devices provide real-time tracking and visibility across the SC. This enhanced visibility improves the accuracy of demand forecasting, enables better decision-making, and improves customer service. Meanwhile, French company Qopius has developed an AI system capable of identifying various elements such as price tags, logos, brands, and labels. Additionally, it can recognize when a shelf is out of stock, helping improve inventory management and store operations (DHL, 2018).

In the realm of agriculture, US machinery maker John Deere employs IBM Watson at its production factory in Mannheim, Germany. Deep Learning-powered cameras are used to detect product faults, and Watson provides explanations to human operators on methods to fix the issues. Workers can even interact with Watson, asking it questions related to the faults. The smart system then automatically orders the correct parts and suggests an optimal time for maintenance, enhancing production efficiency. (DHL, 2018).

The integration of AI and automation has given rise to the concept of "lights out" or dark warehouses. Factories employing this technology use robots with visual perception capabilities to function effectively without traditional lighting. As approximately 30% of energy consumption in warehouses is attributed to lighting (Alim & Kesen, 2020), these energy-efficient dark warehouses contribute to reducing carbon footprints, aligning with the principles of a circular and sustainable economy.

AI also plays a significant role in enhancing product grouping and warehouse optimization based on customer behavior, repeat purchases, and order history. By analyzing seasonality and geographical factors, AI intelligently suggests grouping specific products together, optimizing the efficiency of warehouse operations. This not only improves the overall customer experience but also leads to cost savings in electricity and maintenance expenses.

4.3.2 Predictive Maintenance

Predictive maintenance, also known as prognostic maintenance, is a proactive approach that involves predicting when warehouse machines are likely to break down and recommending timely repairs and maintenance. This strategy significantly reduces downtime and repair costs by detecting microscopic cracks, scratches, and defects in warehouse facilities and production lines Predictive maintenance relies. on predictive analytics, which collects data from sensors to forecast machine breakdowns and duration, ultimately minimizing downtimes and preventing unscheduled repairs. By

Table 3 Summary of AI techniques, use cases, examples and proven benefits in the MAKE stage

Use Cases (RQ2)	AI Techniques (RQ1)	Industry Examples (RQ3)	Beneficial Results (RQ4))
Product Quality Assurance, Smart Warehouse Management	Machine Vision (CNN, Object Recognition, Image/Semantic/Instance Segmentation…), Deep Learning, NLP	IBM's Watson, Metro Cash & Carry, Intel, Alibaba, John Deere	Over 90% accuracy in detecting cargo defects from real-time images (Watson) Correctly classify over 95.5% of data (Metro Cash & Carry) Increase stock handling capacity by up to 3 times while reducing labor costs by 70% (Alibaba) Increase productivity by 20% (with cobots) Improve product quality and operational efficiency, decrease defects, increase productivity, faster decision making, increase profits, decrease fuel consumption, enhance safety
Predictive Maintenance	Deep Learning, RL, Decision Trees	General Electric, Volvo	10% reduction in maintenance costs 20% decrease in annual downtime Decrease repair costs, decrease defect rates, Enhance safety

leveraging Machine Vision and image processing, including Object Identification, Image Recognition, and Instance Segmentation, AI can detect even the tiniest cracks and defects in warehouse infrastructure. The incorporation of small robots with gas sensing capabilities further ensures potential gas leakages are identified promptly and addressed early on.

Predictive maintenance mainly relies on ML applications (Kumar and Hati, 2021), with Deep Learning specifically being applied for predictive fault detection in induction motors (Luo *et al.,* 2019). Other techniques to predict machine failures are RL (Encapera *et al.,* 2021) and Decision Trees (Kaparthi and Bumblauskas, 2020). In a report titled "Smartening up with Artificial Intelligence" published in 2018, global consulting firm McKinsey revealed that predictive AI can lead to a 10% reduction in maintenance costs and up to a 20% decrease in annual downtime (McKinsey, 2018a). These AI-driven advancements in predictive maintenance technology contribute to improved warehouse efficiency, cost savings, & enhanced safety by addressing issues before they escalate and disrupt operations. Molęda (2023) discussed how companies such as US-based MNC General Electric use AI algorithms to predict equipment failures and optimize maintenance schedules, thereby reducing downtime and maintenance costs. Other real-world examples include Swedish carmaker Volvo which has developed a truck type installed with multiple sensors inside to identify when and where maintenance is to be carried out. (DHL, 2016).

4.4 Deliver

4.4.1 Route Optimization

ML and graph theory play a crucial role in determining the most efficient routes for transportation. Leveraging real-time data from in-transit shipments, AI can accurately predict the departure, potential delays, and expected arrival times of cargo. When a critical component shipment is running late, the intelligent system promptly suggests alternative routes, re-routing options, or emergency shipments, all while considering traffic conditions and traffic signal patterns. The impact of AI on logistics and route optimization is evident in cases such as US transport giant FedEx, which uses AI algorithms to optimize delivery routes based on real-time traffic data, weather conditions, and delivery schedules. Loske (2021) highlighted that AI-enabled logistics solutions reduce transportation costs, shorten delivery times, and increase overall customer satisfaction.

GA have been successfully applied for routing optimization in SC, specifically vehicle routing and scheduling (Chen *et al.,* 1998, Park 2001); delivery and pickup (Jung and Haghani, 2000); bus network optimization (Bielli *et al.,* 2002); minimum spanning tree (Zhou and Gen, 1999). Chambers (2001) in fact found out that GA is among the most popular AI methods used to solve network transportation issues. Hill and Böse (2016) discovered that applying an ANN-enabled DSS to design the optimal routing of trucks could lead to a decrease in waiting times and workloads while Michalewicz and Fogel (2004) found that the famous TSP (traveling salesman problem) could be solved using FL.

AI goes beyond route optimization by learning drivers' preferences for specific routes and recommending the most favored paths accordingly. It efficiently manages and allocates drivers to specific routes based on the time of day or month, maximizing resource utilization and productivity. By constantly monitoring the real-time location and conditions of shipments, AI ensures on-time deliveries and dynamically adjusts plans as circumstances change, significantly reducing lead times and the overall carbon footprint. Route optimization powered by AI has been reported to achieve a remarkable 20% reduction in fuel consumption (Jovičić *et al.,* 2011). This is in part assisted by satellite imagery firms among which is

DigitalGlobe that provides high-resolution images of the earth's surface, offering valuable input and insights. Its satellites can identify lane information and new road markings even before they are officially updated on the maps.

In other industry cases, UPS leverages ML to anticipate weather turbulence and recommends alternative routes accordingly. Through UPS' On-Road Integrated Optimization and Navigation system, the company calculates the most efficient path for road deliveries. By utilizing ML algorithms, UPS can dynamically adjust delivery routes based on real-time weather data, ensuring timely and reliable deliveries even in the face of challenging weather conditions. This predictive and prescriptive approach enables UPS to optimize its operations, minimize disruptions, and enhance overall customer satisfaction.

In other instances, DHL and Chinese smartphone maker Huawei collaborated to develop a sensor system installed inside mailboxes. These sensors relay information to the nearest or "most optimal" DHL drivers, allowing for more efficient pickups and reducing drivers' waiting times by an impressive 50% (Alim & Kesen, 2020). These advancements in AI-driven technologies are revolutionizing transportation and logistics, leading to enhanced efficiency and sustainability.

4.4.2 Dynamic Pricing

Dynamic pricing, unlike fixed pricing, allows for flexibility, ensuring that prices accurately reflect the current market conditions, optimizing profits. It is a powerful AI use case that involves continuously adjusting prices based on various factors, such as demand, seasonality, social media trends, time of the day (time-based pricing), weather conditions, competitors' prices, and individual shopping habits.

Leung *et al.* (2019) proposed applying FL to enable dynamic pricing that resulted in an increase in quotes acceptance rate by 78% and a 60% reduction in the average planning time of offers. AI enables personalized pricing by analyzing customer data to tailor prices based on individual preferences and purchase history. Amazon uses AI algorithms to recommend personalized prices to customers, improving customer experience and increasing sales (Chen *et al.,* 2016) while American Delta Airlines leverages AI to analyze real-time data such as demand, competitor prices, and historical sales to dynamically adjust ticket prices.

This ensures that products are competitively priced while maximizing returns. E-commerce platforms like eBay also use AI to adjust prices in real time based on factors such as customer behavior, competitor pricing, and product availability. This approach allows sellers to quickly adapt to market conditions and optimize their revenue potential (Hann, 2006). Dynamic pricing has been considered for the tourism sector (Guizzardi *et al.,* 2021) with the hotel industry applying AI-based revenue management systems to optimize pricing for hotel rooms, event spaces, and other offerings. For example, US-headquartered hotel chain Marriott uses AI algorithms to adjust prices based on factors such as occupancy, seasonality, and local events (Kardaras *et al.,* 2013).

Not limited to service providers, commodity firms also leverage AI-prescribed dynamic pricing through ESL (Electronic Shelf Labelling), allowing them to instantly adjust product prices based on AI recommendations. Prominent companies like Compass Marketing, in collaboration with Panasonic, are actively working on innovations like Powershelf, which facilitate instant price adjustments within minutes and from remote locations. As AI-driven dynamic pricing proves its effectiveness and efficiency, traditional static pricing is expected to take a back seat in the future. The gradual shift towards dynamic pricing will enable businesses to adapt quickly to market changes and optimize their revenue streams effectively.

4.4.3 Last Mile Delivery, Customer Service

AI applications have become pervasive throughout the SC, spanning from the procurement stage to the final delivery. Even LMD (last-mile delivery) and customer service are benefiting from AI technologies. Automatic delivery utilizes a combination of AI methods namely GA and ANN for route optimization; CNN, Object Recognition, Image Segmentation…for Machine Vision to recognize objects; and NLP for communication (Chen *et al.,* 1998; Park, 2001; Jung and Haghani, 2000; Bielli *et al.,* 2002; Zhou and Gen, 1999; Chambers, 2001; Hill and Böse 2016).

In this domain, Google has made remarkable strides through its Wing unit, which has successfully completed 330,000 drone deliveries. Walmart has also entered the AI-driven delivery arena, partnering with Zipline for 600,000 air deliveries, primarily focused on medical supplies in Africa. Meanwhile, Amazon has ambitious plans for 10,000 drone deliveries in 2023, despite having executed only 100 so far (Tarasov, 2023). These autonomous drone delivery systems leverage AI to avoid collisions with other drones and navigate around obstacles such as power lines and tall buildings, ensuring efficient and safe operations. UPS has also collaborated with Zipline to deliver medical supplies via drones in Rwanda. On the ground, AI-powered delivery solutions are transforming the food industry. Google teamed up with Chipotle industry. Google teamed up with Chipotle to deliver burritos at Virginia Tech, while US pizza restaurant chain Domino's Pizza partnered with Flirtey for pizza delivery in New Zealand. Additionally, Domino's has joined forces with Nuro, a California-based firm, to deliver pizzas in Houston, Texas, using Nuro's autonomous cars (Wood, 2021).

Many firms have employed or are considering using autonomous vehicles. Amazon is a prominent player in this race. In 2020, the company made a significant move by acquiring Zoox, a self-driving startup, for a staggering $1.2 billion Since 2016, Amazon has been actively exploring drone deliveries, aiming to achieve swift deliveries within 30 minutes. Meanwhile, Google's Waymo unit is also making strides in the autonomous vehicle domain. In 2020, Waymo announced a total of $3.2 billion in funding for investments in self-driving vehicles (Feiner, 2021). Waymo is developing driverless trucks and anticipates revenues of US$114 billion by 2030 (Waymo, 2020).

In the food industry, US-based restaurant KiwiBot utilizes AI-powered robots to deliver meals, harnessing behavioral neural networks to optimize the delivery

Table 4 Overview of AI techniques, use cases, examples and proven benefits in the DELIVER stage

Use Cases (RQ2)	AI Techniques (RQ1)	Industry Examples (RQ3)	Beneficial Results (RQ4))
Route Optimization	GA, ANN, FL	FedEx, UPS (On-Road Integrated Optimization and Navigation), DHL & Huawei	Cut drivers' waiting times by 50% (DHL & Huawei) Reduce fuel consumption by 20% Reduce costs, Decrease lead times, Enhanced customer satisfaction
Dynamic Pricing	FL	Delta Airlines, Amazon, eBay, Marriott	Increase in quotes acceptance rate by 78% 60% reduction in average planning time of offers. Increase profits, More sales
Last Mile Delivery, and Customer Service	GA, ANN, Machine Vision (CNN, Object Recognition, Image Segmentation…), NLP	Google, Walmart, UPS, Domino's Pizza, McDonald, DHL, Home (Google), Alexa (Amazon), Cortana (Microsoft), Siri (Apple)	Automatic delivery Increase Customer satisfaction (voice app, chatbots) Reduce operational costs by up to 70% (Jenny) Shorten lead times, better understand customer, better CRM

process and improve customer service. Furthermore, Google's self-driving car system has been officially recognized as a driver in the US. According to a survey conducted by Grace *et al.,* (2018), respondents predict that AI will surpass human performance in driving trucks by 2027, and there is a 50% likelihood of AI automating all human jobs within 120 years. Autonomous vehicles utilize advanced Deep Learning algorithms and sensing technologies to process real-time incoming data. Through these sophisticated systems, they can identify crucial elements such as street markings, road signs, obstacles, and traffic signals, enabling safe and efficient autonomous navigation on the roads.

To enhance customer satisfaction, businesses utilize NLP-assisted chatbots like ChatGPT that possess the ability to comprehend human languages and nuances, providing instant responses to customer queries 24/7. NLP employs statistical methods to analyze word phrases and and patterns in speech or text, even understanding jargon in different contexts and evolving as these jargons change over time. NLP are ubiquitously used in AI chatbots to answer customer queries and execute direct sales (Zdravković *et al.,* 2022; Toorajipour *et al.,* 2021). AI plays a crucial role in analyzing customer behavior data, such as idle time spent browsing the web and sentiment variations during different hours. This analysis enables AI to suggest the most opportune and receptive moments for engaging customers in product recommendation discussions.

AI-powered sentiment analysis tools such as Lexalytics analyze customer feedback from social media, reviews, and surveys to measure customer sentiment toward products and services. Starbucks also uses sentiment analysis to understand customer reactions to new menu items and promotions, allowing them to tailor their offerings based on feedback. Since personalization increases customer engagement and conversion (Bleier *et al.,* 2018), Amazon's recommendation engine uses AI algorithms to analyze browsing and purchase history to suggest relevant products. Companies are also using guided AI to analyze call center records and customer interactions. For example, Delta Airlines uses AI to transcribe customer calls and identify trends and concerns while US fast food chain McDonald's uses AI kiosks to suggest additional items based on customer orders, resulting in increased sales (Chicago Tribune, 2019).

AI-powered apps like Google's Home, Amazon's Alexa, Microsoft's Cortana, and Apple's Siri facilitate product searches and purchases through voice commands, streamlining the shopping process. Innovative applications of AI in the retail industry extend to companies like Sephora, which leverages the AI-powered Visual Artist program. This program suggests cosmetic products tailored to each customer's facial features using computer vision and Augmented Reality (Kumar *et al.,* 2018).

In the realm of brick-and-mortar stores, Amazon Go has introduced an AI-driven shopping experience. Shoppers check in at the store, place products in their carts, and can leave without the need to pay at the checkout counter. The store's system of cameras detects the products chosen by the shopper, debits their accounts, and emails the receipts accordingly, revolutionizing the traditional shopping process. In the future, supermarkets could implement AI systems that leverage cameras to analyze shopper behavior. For instance, if a customer places a bottle of wine in their cart, AI could suggest other similar products like beer or beef to pair with the wine and direct the shopper to the corresponding shelves, potentially through a video screen on the cart.

In 2017, DHL Parcel introduced a voice-based service to track LMD using Amazon's Alexa. Through an Echo speaker, customers can inquire about their product's whereabouts and expected delivery time. By simply speaking their tracking number, the Echo speaker provides them with the latest shipment information. Moreover, customers have the option to request Alexa to transfer their queries to human operators for further assistance. Another innovative conversational AI, "Jenny," developed by Israel's package.ai, interacts with customers via SMS or Facebook Messenger to gather instructions on a convenient pickup time and location, as well as confirmations. Jenny also keeps delivery drivers updated on any last-minute changes and collects feedback from parcel recipients. The startup claims that its chat-based smart system can significantly reduce operational costs by up to 70% (DHL, 2018). Thanks to those ingenious CRM algorithms, Deb *et al.* (2018) argue that retailers can now anticipate their customers' desires even before the customers themselves are aware of their true preferences.

5. SUMMARY, DISCUSSIONS AND FUTURE RESEARCH

This study provides an overview of various AI applications and real-world examples in SCM. We found out that AI is used widely across all four stages of the SCOR model, especially in the first stage PLAN. To answer RQ1, the most commonly used AI techniques include NN, ANN, CNN, RNN, GA, SVM, RL, FL, NLP, Decision trees, Object Recognition, and Image Segmentation. For RQ2, significant benefits are found across the 4 SC processes, namely PLAN (demand forecasting, inventory optimization, supply risk mitigation), SOURCE (procurement, supplier selection), MAKE (product quality assurance, smart warehouse management, predictive maintenance), and DELIVER (route optimization, dynamic pricing, and LMD, and customer service).

Addressing RQ3, industry examples include DHL, IBM, DM, Otto, UPS, Walmart, Amazon, Nike, Google, Microsoft, Apple and Alibaba while practical benefits of applying AI in SCM (RQ4) are enhanced SC efficiencies, lower costs, higher profits, improved customer satisfaction, time saving, reduced potential SC disruption, better suppliers/customers relationships, improved product quality and operational efficiency, faster decision making, enhanced safety, and shorter lead times, among others.

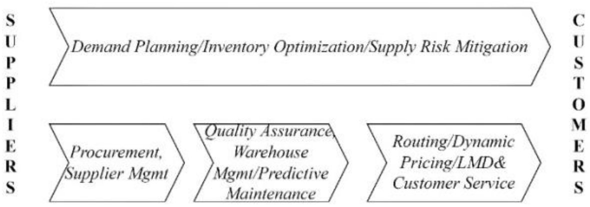

Figure 3 AI use cases in SCM according to SCOR.

Despite our best efforts, this study has several limitations one of which lies in its methodology. This is a review paper lacking empirical evidence or primary data. Case studies with in-depth analysis and expert interviews are needed to gain further insights into this topic. Since we use Google search for industry cases and for gray literature which leads to thousands, if not more, hits, it is almost impossible to check all results and we may not be exhaustive. Besides, Google search algorithms are personalized, hence each search result is different and based on previous searches, hence results could be biased.

Although we try to be as inclusive as possible, this paper should be treated as a supplementary overview and not as a systematic or exhaustive research. Also, we could miss many new hybrid AI techniques or simply fail to capture them all since the field is so vast and evolving day by day. We also do not address the RETURN stage of the SCOR model since we consider it the reverse side of the four treated stages but we may be wrong and there could be different AI applications and use cases in this "return" process. Future studies could explore this aspect. In addition, we do not include failed instances as companies only publish successful applications and may not report unsuccessful ones. Besides, not many corporations publish their AI application results and those that do tend to be biased towards giant consultancies and MNCs.

In the future, research could focus on AI adoption challenges. Singh *et al.,* (2022) cited them as system interoperability, scalability, training cost, operational costs and called for further study into this topic. Then a study on the RETURN processes should be done since there could be different AI applications and use cases in this "return" stage. Case studies with in-depth analysis and expert interviews to gain further insights into this topic are another direction for upcoming research. Then, the integration of AI and blockchain technology into SCM is anticipated. Wang *et al.* (2019) list blockchain's numerous benefits in SCM. Though blockchain in SCM is highly effective and the combination of AI and blockchain in SCM could be highly synergistic (Dinh & Thai, 2018; Zheng *et al.,* 2019; Rodriguez *et al.* 2020), the field is in its nascent stage. Tsolakis *et al.* (2022) conducted a systematic literature review and found only five works exploring AI-blockchain integration in SCM, which as such could serve as another fertile ground for future study.

With companies like Unilever serving as pioneers in driving initiatives for a more environmentally friendly and sustainable SC, greening the SC by leveraging AI is one potential research avenue. However, despite progress in Industry 4.0, the implementation of smart Cyber-Physical Systems (CPS) and the IoT also raises ethical concerns. Accusations have been made against Amazon for treating employees like robots. Whistleblowers expose the use of extensive tracking software, thermal scanners, wristbands, and scanning machines to monitor employee activities. Managers are notified if employees are idle for more than 18 minutes per shift, even during breaks such as drinking water or using the restroom (Brintrup, 2023). Therefore, further study on AI ethics in SCM is recommended.

Additionally, research into human trust in AI within the SC context is essential, given its mixed track record. From deadly accidents involving automated vehicles (Lubben, 2018) to rising AI models like ChatGPT generating convincing fake information (Faisal, 2023), trust has been undermined. Additionally, biases in data input and algorithms (Asan, 2020) also influence trust. Addressing these ethical concerns is crucial to ensure the successful and responsible implementation of AI in the SC and other domains.

6. CONCLUSION

Driven by the growing complexity and uncertainty in global supply chains, this study explores how AI can enhance performance, resilience, and decision-making. Taking a practical perspective, it examines commonly used AI techniques, real-world applications, and their benefits, using the SCOR framework—plan, source, make, deliver—for clarity and relevance. For RQ1, we identified key techniques such as neural networks, genetic algorithms, SVM, reinforcement learning, fuzzy logic, and NLP. RQ2 shows AI is widely applied across all SCOR stages: PLAN (demand forecasting, inventory optimization, supply risk mitigation), SOURCE (procurement, supplier selection), MAKE (product quality assurance and warehouse management, predictive maintenance), and DELIVER (route optimization, dynamic pricing, last-mile delivery and customer service). RQ3 highlights adoption by multinationals and smaller firms alike, while RQ4 reveals benefits such as efficiency, cost savings, better service, and faster operations. This is the first study to integrate theory with practice by mapping specific AI methods, use cases, and outcomes to SCOR. It contributes theoretically by linking AI to supply chain results, and practically by offering actionable insights for firms adopting AI.

ACKNOWLEDGEMENTS

The authors wish to thank the Internal grant agency FaME TBU No. IGA/FaME/2025/004 for its support

DECLARATION OF INTEREST

The authors declare that they have no known competing interests

ABBREVIATIONS

AIS = Automatic Identification System
ANN = Artificial Neural Networks
ANP = Analytic Network Process
ARIMA = Autoregressive Integrated Moving Average
CNN = Convolutional Neural Network
CNN = Convolutional Neural Networks
CRM = Customer relationship management
DEA = Data Envelopment Analysis
DHL = Dalsey Hillblom Lynn
DM = Drogerie Markt
DNN = Deep Neural Network
DSS = Decision Support System
ERP = Enterprise Resource Planning
ESL = Electronic Shelf Labelling
FL = Fuzzy Logic
GA = Genetic Algorithms
IoT = Internet of Things
JIT = Just in Time
KPIs = Key Performance Indicators
MCDM = Multicriteria Decision-Making
ML = Machine Learning
MNC = multinational corporation
NLP = Natural Language Processing
NN = Neural Networks
OLAP = Online analytical processing
RFID = Radio Frequency Identification
RL = Reinforcement Learning
RNN = Recurrent Neural Networks
RQ = Research Question
SC = supply chain
SCM = Supply Chain Management
SCOR = Supply-chain operations reference
SKU = Stock Keeping Unit
SVM = Support Vector Machines
TSP = Traveling Salesman Problem
UPS = United Parcel Service
WOS = Web of Science

REFERENCES

Alım, M., & Kesen, S. E. (2020). *Smart Warehouses in Logistics 4.0. In Logistics* (pp. 186–201). https://doi.org/10.1201/9780429327636-22

Arsene, C. (2022). *Six Reasons Executives Should Invest in AI in Supply Chain. Digital Authority Partners*. https://www.digitalauthority.me/resources/ai-supply-chain-strategy/

Asan, O., Bayrak, A. E., & Choudhury, A. (2020). Artificial intelligence and human trust in healthcare: Focus on clinicians. *Journal of Medical Internet Research*, 22(6), e15154. https://doi.org/10.2196/15154

Babai, M. Z, Arampatzis M, Hasni M, Lolli F, Tsadiras A. (2025). On the use of machine learning in supply chain management: a systematic review, *IMA Journal of Management Mathematics*, Volume 36, Issue 1, January 2025, Pages 21–49, https://doi.org/10.1093/imaman/dpae029

Balan, S., Vrat, P., and Kumar, P., (2007). Reducing the Bullwhip effect in a supply chain with fuzzy logic approach. *International Journal of Integrated Supply Management*, 3 (3), 261–282.

Bielli, M., Caramia, M., and Carotenuto, P., (2002). Genetic algorithms in bus network optimization. *Transportation Research Part C*, 10, 19–34.

Binns, J. (2018). *What the Fidget Spinner Fad Can Teach Logistics About the Need for AI*, Sourcing Journal. https://sourcingjournal.com/topics/technology/dhl-ibm-ai-logistics103446-103446/

Bleier, A., De Keyser, A., Verleye, K. (2018). Customer Engagement Through Personalization and Customization. In: Palmatier, R., Kumar, V., Harmeling, C. (eds) *Customer Engagement Marketing. Palgrave Macmillan*, Cham. https://doi.org/10.1007/978-3-319-61985-9_4

Bloomberg, (2023). *Walmart Is Using AI to Negotiate the Best Price With Some Vendors*, https://www.bloomberg.com/news/articles/2023-04-26/walmart-uses-pactum-ai-tools-to-handle-vendor-negotiations?srnd=premium&leadSource=uverify%20wall#xj4y7vzkg

Boualam M. (2023). *The Transformative Power of AI in Supply Chain Management*, SCMGLOBE, https://www.scmglobe.com/the-transformative-power-of-ai-in-supply-chain-management/

Brintrup, A. & George B., & Ashutosh T., & Svetan R., & Giovanna M., & Jatinder S. (2023). *Trustworthy, responsible, ethical AI in manufacturing and supply chains: synthesis and emerging research questions*. ARXIV. https://arxiv.org/abs/2305.11581

Burgess, A. (2018). *The Executive Guide to Artificial Intelligence*. In Springer eBooks. https://doi.org/10.1007/978-3-319-63820-1

Cannas, V. G., Ciano, M. P., Saltalamacchia, M., & Secchi, R. (2023). Artificial intelligence in supply chain and operations management: a multiple case study research. *International Journal of Production Research, 62*(9), 3333–3360. https://doi.org/10.1080/00207543.2023.2232050

Carbonneau, R. A., Laframboise, K., & Vahidov, R. (2008). Application of machine learning techniques for supply chain demand forecasting. *European Journal of Operational Research, 184*(3), 1140–1154. https://doi.org/10.1016/j.ejor.2006.12.004

Carrera, D.A. and Mayorga, R.V., (2008). Supply chain management: a modular fuzzy inference system approach in supplier selection for new product development. *Journal of Intelligent Manufacturing, 19* (1), 1–12.

Carrington, D. (2016). *Wimbledon tennis balls travel over 50,000 miles to arrive at centre court*. The Guardian. https://www.theguardian.com/environment/damian-carrington-blog/2013/jun/26/wimbledon-tennis-balls-miles-centre-court

Chambers, L., (2001). *The practical handbook of genetic algorithms: applications*. 2nd ed. Boca Raton, FL: Chapman & Hall/CRC. https://doi.org/10.1201/9781420035568

Charles, V., Emrouznejad, A and Gherman, T (2023). *A critical analysis of the integration of blockchain and artificial intelligence for supply chain, ANNALS OF OPERATIONS RESEARCH*

Chehbi-Gamoura, S., Derrouiche, R., Damand, D., & Barth, M. (2019). Insights from big Data Analytics in supply chain management: an all-inclusive literature review using the SCOR model. *Production Planning & Control,* 31(5), 355–382. https://doi.org/10.1080/09537287.2019.1639839

Chen, L, Mislove, A and Wilson, C. (2016). An Empirical Analysis of Algorithmic Pricing on Amazon Marketplace. In Proceedings of the 25th International Conference on World Wide Web (WWW '16). *International World Wide Web Conferences Steering Committee, Republic and Canton of Geneva*, CHE, 1339–1349. https://doi.org/10.1145/2872427.2883089

Chen, X., Wan, W., and Xu, X., (1998). Modeling rolling batch planning as a vehicle routing problem with time windows. *Computers and Operations Research, 25* (12), 1127–1136.

Chicago Tribune (2019). *McDonald's is turning to artificial intelligence to get you to spend more in the drive-thru*, https://www.chicagotribune.com/business/ct-biz-mcdonalds-acquires-dynamic-yield-artificial-intelligence-20190325-story.html

Dale M. (2018). Automating grocery shopping. Imaging and Machine Vision Europe, 85, 16. Davenport, T.H. *The AI Advantage: How to Put the Artificial Intelligence Revolution to Work.*

Darvazeh, S. S., Vanani, I. R., & Musolu, F. M. (2020). *Big Data Analytics and its applications in supply chain management.* In IntechOpen eBooks. https://doi.org/10.5772/intechopen.89426

Deb, Suman & Jain, Ruchi & Deb, Varsha. (2018). *2018 8th International Conference on Cloud Computing, Data Science & Engineering (Confluence), Noida, India, 2018*, pp. 758-764. https://ieeexplore.ieee.org/document/8442900

Deepika (2023). *Applications and Risks of AI in Supply Chain Management, NIMBUSPOST*. https://nimbuspost.com/blog/applications-and-risks-of-ai-in-supply-chain-management/#

Derfoufi Ghita, Benrrezzouq Rhizlane (2024). *Integrating AI and SCOR model in supply chain management*. (2024). In IRTESH (Vol. 1, Issue 3). https://irtesh.org/wp-content/uploads/2024/09/Ghita-DERFOUFI_IRTESH2024.pdf

DHL (2016). Robotics in Logistics. *A DPDHL perspective on implications and use cases for the logistics industry*. Bonn, Germany. Available at https://www.dhl.com/content/dam/downloads/g0/about_us/logistics_insights/dhl_trendr eport_robotics.pdf.

DHL (2018). *ARTIFICIAL INTELLIGENCE. IN LOGISTICS. A collaborative report by DHL and IBM on implications and use cases for the logistics industry*, http://www.globalhha.com/doclib/data/upload/doc_con/5e50c53c5bf67.pdf

DHL (2019). *DHL ADDS LATEST AI ADVANCEMENTS TO THE RESILIENCE360 PLATFORM*, https://www.dhl.com/global-en/home/press/press-archive/2019/dhl-adds-latest-ai-advancements-to-the-resilience360-platform.html

Dinh T and M. Thai, (2018). *AI and Blockchain: A Disruptive Integration. In Computer*, vol. 51, no. 09, pp. 48-53, 2018. doi: 10.1109/MC.2018.3620971

Dundas, S. (2018). *This Holiday Season, Speks Aims To Fill The Fidget Spinner Void. Forbes*. https://www.forbes.com/sites/suziedundas/2018/11/27/this-holiday-season-speks-aims-to-fill-the-fidget-spinner-void/?sh=5d5b56c269c0

Ehrenthal, J. C. F., Gachnang, P., Loran, L., Rahms, H., & Schenker, F. (2024). Integrating Generative Artificial Intelligence into Supply Chain Management Education Using the SCOR Model. *In Lecture notes in business information processing* (pp. 59–71). https://doi.org/10.1007/978-3-031-61003-5_6

Encapera, A., Gosavi A., and Susan L. Murray. (2021). Total Productive Maintenance of Make-to-Stock Production-Inventory Systems via Artificial-IntelligenceBased ISMART. *International Journal of Systems Science: Operations & Logistics* 8 (2): 154–166. https://www.tandfonline.com/doi/abs/10.1080/23302674.2019.1707906

Feiner, L. (2021). *Alphabet's self-driving car company Waymo announces $2.5 billion investment round. CNBC*. https://www.cnbc.com/2021/06/16/alphabets-waymo-raises-2point5-billion-in-new-investment-round.html

Felea, Mihai; Albăstroiu, Irina (2013). Defining the Concept of Supply Chain Management and its Relevance to Romanian Academics and Practitioners, Amfiteatru Economic Journal, ISSN 2247-9104, *The Bucharest University of Economic Studies, Bucharest*, Vol. 15, Iss. 33, pp. 74-88

Freeman, M. (2021). *Qualcomm beefs up artificial intelligence team with purchase of Twenty Billion Neurons, San Diego Union Tribune*. https://www.sandiegouniontribune.com/business/technology/story/2021-07-19/qualcomm-beefs-up-artificial-intelligence-team-with-asset-purchase-of-twenty-billion-neurons

Grace, K., Salvatier, J., Dafoe, A., Zhang, B., & Evans, O. (2018). Viewpoint: When will AI exceed human performance? Evidence from AI experts. *Journal of Artificial Intelligence Research*, 62, 729–754.

Guizzardi, A., Pons, F., Angelini, G., & Ranieri, E. (2021). Big data from dynamic pricing: A smart approach to tourism demand forecasting. *International Journal of Forecasting*, 37(3), 1049–1060. https://doi.org/10.1016/j.ijforecast.2020.11.006

Hann, I. H., Hinz, O., & Spann, M. (2006). Dynamic Pricing in Name-Your-Own-Price Channels: Bidding Behavior, Seller Profit and Price Acceptance. *In Workshop on Information Systems and Economics (WISE2006)*.

Harrir, M. M., & Sari, L. T. (2024). Exploring the Power of Artificial intelligence in Supply Chain Management: A literature review on the artificial intelligence applications and tools used in supply chains and their distribution According to the SCOR Method. *Engineering Management Journal*, 1–22. https://doi.org/10.1080/10429247.2024.2406125

Helo, P and Hao, YQG (2022). Artificial intelligence in operations management and supply chain management: an exploratory case study, *Production Planning & Control*, 33:16, 1573-1590, DOI: 10.1080/09537287.2021.1882690

Hill, A., and Böse J.W. (2016). A Decision Support System for Improved Resource Planning and Truck Routing at Logistic Nodes. *Information Technology and Management* 18: 241–251.

https://link.springer.com/article/10.1007/s10799-016-0267-3

Hirvonen-Ere, S. (2023). Contract Lifecycle Management as a Catalyst for Digitalization in the European Union. *In Digital Development of the European Union: An Interdisciplinary Perspective* (pp. 85-99). Cham: Springer International Publishing.

Jovičić, N. M., Bošković g. B., Vujić Goran v., Jovičić Gordana r., Despotović Milan z., Milovanović Dobrica m., and Gordić Dušan r. (2011). *Route optimization to increase energy efficiency and reduce fuel consumption of communal vehicles*. ResearchGate. https://www.researchgate.net/publication/228649815_Route_optimization_to_increase_energy_efficiency_and_reduce_fuel_consumption_of_communal_vehicles

Jung, S. and Haghani, A., (2000). A genetic algorithm for pick-up and delivery problem with time windows. *Journal of Transportation Research Board*, 1733, 1–7.

Juricek, J. E. (2009). Access to Grey Literature in Business: An exploration of Commercial white Papers. *Journal of Business & Finance Librarianship*, 14(4), 318–332. https://doi.org/10.1080/08963560802365388

Kamble, S. S., Mor, R. S., & Belhadi, A. (2023). Big Data Analytics for Supply Chain Transformation: A Systematic Literature Review using SCOR Framework. *In EAI/Springer Innovations in Communication and Computing* (pp. 1–50). https://doi.org/10.1007/978-3-031-19711-6_1

Kaparthi, S., and Bumblauskas D. (2020). Designing Predictive Maintenance Systems Using Decision TreeBased Machine Learning Techniques. *International Journal of Quality & Reliability Management* 37 (4): 659–686. https://doi.org/10.1108/IJQRM-04-2019-0131.

Kardaras, D.K., Mamakou, X.J., Karakostas, B., Gkourakoukis, G. (2013). An Approach to Hotel Services Dynamic Pricing Based on the Delphi Method and Fuzzy Cognitive Maps. In: Papadopoulos, H., Andreou, A.S., Iliadis, L., Maglogiannis, I. (eds) Artificial Intelligence Applications and Innovations. AIAI 2013. *IFIP Advances in Information and Communication Technology*, vol 412. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-41142-7_56

Khan, M. M., Bashar, I., Minhaj, G. M., Wasi, A. I., & Hossain, N. U. I. (2023). Resilient and sustainable supplier selection: an integration of SCOR 4.0 and machine learning approach. *Sustainable and Resilient Infrastructure*, 8(5), 453–469. https://doi.org/10.1080/23789689.2023.2165782

Korolov, M. (2018). *AI in the supply chain: Logistics gets smart. CIO*. https://www.cio.com/article/228833/ai-in-the-supply-chain-logistics-get-smart.html

Kosasih, EE and Brintrup, A (2022). A machine learning approach for predicting hidden links in supply chain with graph neural networks. *INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH*

Kumar N., Katoch S., Tripathi S., Singh B. P., Sajal S. and Yadav A. L., (2023). "AI Enabled Invoice Management Application," *2023 8th International Conference on Communication and Electronics Systems (ICCES)*, Coimbatore, India, 2023, pp. 816-820, doi: 10.1109/ICCES57224.2023.10192802.

Kumar, K.S., Tamilselvan, S., & Sha B. (2018). Artificial Intelligence Powered Banking Chatbot. *International Journal of Engineering Science and Computing*.

Kumar, P., and Hati A. S. (2021). Review on Machine Learning Algorithm Based Fault Detection in Induction Motors. *Archives of Computational Methods in Engineering* 28 (3): 1929–1940.
https://link.springer.com/article/10.1007/s11831-020-09446-w

Kuo, R.J.,Y.C. Wang, and F.C.Tien (2010). Integration of Artificial Neural Network and MADA Methods for Green Supplier Selection. *Journal of Cleaner Production 18* (12): 1161–1170. https://doi.org/10.1016/j.jclepro.2010.03.020.

Leavy, B. (2023). *Integrating AI into business processes and corporate strategies to enhance customer value, Strategy & Leadership*, Vol. 51 No. 2, pp. 3-9. https://doi.org/10.1108/SL-01-2023-0013

Lehmacher, W. (2021). Digitizing and Automating Processes in Logistics. In: Wurst, C., Graf, L. (eds) *Disrupting Logistics. Future of Business and Finance*. Springer, Cham. https://doi.org/10.1007/978-3-030-61093-7_2

Leung, K.H., Luk, C.C. Choy K.L., Lam H.Y., MLee (2019). A B2B Flexible Pricing Decision Support System for Managing the Request for Quotation Process Under E-Commerce Business Environment, *International Journal of Production Research* 57 (20): 6528–6551. https://doi.org/10.1080/00207543.2019.1566674.

Lima-Junior F.R, Carpinetti L. (2019). Predicting supply chain performance based on SCOR® metrics and multilayer perceptron neural networks, *International Journal of Production Economics*, Volume 212, https://doi.org/10.1016/j.ijpe.2019.02.001.

Lingam, Y. K. (2018). *The role of Artificial Intelligence (AI) in making accurate stock decisions in E-commerce industry*. Int. J. Adv. Res. Ideas Innov. Technol, 4(3), 2281-2286.

Lomas N (2014). *Amazon Patents "Anticipatory" Shipping — To Start Sending Stuff Before You've Bought It, Techcrunch*. https://techcrunch.com/2014/01/18/amazon-pre-ships/

Loske, D., & Klumpp, M. (2021). Human-AI collaboration in route planning: An empirical efficiency-based analysis in retail logistics. *International Journal of Production Economics*, 241, 108236.

Lubben A. (2018). *Self-driving Uber killed a pedestrian as human safety driver watched*, Vice News. https://www.vice.com/en/article/self-driving-uber-killed-a-pedestrian-as-human-safety-driver-watched/

Luo, B., Wang H., Liu H., Li B., and Peng F. (2019). Early Fault Detection of Machine Tools Based on Deep Learning and Dynamic Identification. *IEEE Transactions on Industrial Electronics* 66 (1): 509–518. https://doi.org/10.1109/TIE.2018.2807414.

Marr, B. (2017). *Data strategy: How to profit from a world of big data, analytics and the internet of things*. Kogan Page Publishers. https://dl.acm.org/doi/book/10.5555/3153872

Mazali, T., & Gay, N. (2022). Performed Subjectivities in Ranking and Recommendation Systems. In book: *Digital Platforms and Algorithmic Subjectivities* (pp.213-224)

McKinsey (2017). *Artificial Intelligence the next digital frontier*, https://www.mckinsey.com/~/media/mckinsey/industries/advanced%20electronics/our%20insights/how%20artificial%20intelligence%20can%20deliver%20real%20value%20to%20companies/mgi-artificial-intelligence-discussion-paper.ashx

McKinsey (2018a). *Smartening up with Artificial Intelligence*, https://www.mckinsey.com/~/media/mckinsey/industries/semiconductors/our%20insights/smartening%20up%20with%20artificial%20intelligence/smartening-up-with-artificial-intelligence.ashx

McKinsey (2018b). *Notes from the AI frontier: Insights from hundreds of use cases*, https://www.mckinsey.com/~/media/mckinsey/featured%20insights/artificial%20intelligence/notes%20from%20the%20ai%20frontier%20applications%20and%20value%20of%20deep%20learning/notes-from-the-ai-frontier-insights-from-hundreds-of-use-cases-discussion-paper.ashx

Mendonça, G. D., & Lima, O. F., Junior. (2023). Artificial intelligence applied to supply chain operations management: a systematic literature review. *International Journal of Logistics Systems and Management*, 45(1), 1. https://doi.org/10.1504/ijlsm.2023.130970

MHI (2015). *Supply Chain Innovation, making the impossible possible, MHI Industry Report*, https://supplychainandlogistics.org/wp-content/uploads/2015/03/mhi_industry_report_2015.pdf

Michalewicz, Z., & Fogel, D. B. (2004). *How to solve it: modern heuristics*. In Springer eBooks. https://doi.org/10.1007/978-3-662-07807-5

Min H. (2010). Artificial intelligence in supply chain management: theory and applications, *International Journal of Logistics: Research and Applications*, 13:1, 13-39, DOI: 10.1080/13675560902736537

Mogre, R., Talluri, S. S., & Damico, F. (2016). A decision framework to mitigate supply chain risks: An application in the offshore-wind industry. *IEEE Transactions on Engineering Management*, 63(3), 316–325.

Molęda, M., Małysiak-Mrozek, B., Ding, W., Sunderam, V., & Mrozek, D. (2023). From Corrective to Predictive Maintenance—A Review of Maintenance Approaches for the Power Industry. *Sensors*, 23(13), 5970.

Mourtzis, D., & Doukas, M. (2015). On the configuration of supply chains for assemble-to-order products: Case studies from the automotive and the CNC machine building sectors. *Robotics and Computer-integrated Manufacturing*, 36, 13–24. https://doi.org/10.1016/j.rcim.2015.02.009

Musgrove A., (2020). *Berlin's scoutbee gets $60 million to transform industries with AI-based supplier discovery*, TECH.EU. https://tech.eu/2020/01/20/berlins-scoutbee-gets-60-million-to-transform-industries-with-ai-based-supplier-discovery/

Ntabe, E. N., LeBel, L., Munson, A. D. & Santa-Eulalia, L.-A. (2015). A systematic literature review of the supply chain operations reference (SCOR) model application with special attention to environmental issues. *Int. J. Prod. Econ.*, 169, 310–332.

Ozdogru, Unsal. (2020). Impact of exponential technologies on global supply chain management, Editor(s): Anthony M. Pagano, Matthew Liotine, *Technology in Supply Chain Management and Logistics*, Elsevier, 2020, Pages 37-56, ISBN 9780128159569

Park, B.-Y., (2001). A hybrid genetic algorithm for the vehicle scheduling problem with due times and time deadlines. *International Journal of Production Economics*, 73 (2), 175–188.

Patyane, N. (2023). *Artificial intelligence in supply chain management, TIMES of INDIA*. https://timesofindia.indiatimes.com/readersblog/only-thoughts/artificial-intelligence-in-supply-chain-management-52305/

Paul, S., Azeem, A (2011). An artificial neural network model for optimization of finished goods inventory. *International Journal of Industrial Engineering Computations*. https://www.growingscience.com/ijiec/Vol2/IJIEC_2011_3.pdf

Petrova, M. (2018). *We traced what it takes to make an iPhone, from its initial design to the components and raw materials needed to make it a reality. CNBC*. https://www.cnbc.com/2018/12/13/inside-apple-iphone-where-parts-and-materials-come-from.html

Piasecki, J., Waligora, M. & Dranseika, V. (2018). Google Search as an Additional Source in Systematic Reviews. *Sci Eng Ethics 24*, 809–810 (2018). https://doi.org/10.1007/s11948-017-0010-4

Pournader, M. Ghaderi H., Hassanzadegan A., Fahimnia B. (2021). Artificial intelligence applications in supply chain management, *International Journal of Production Economics*, Volume 241, 108250, ISSN 0925-5273, https://doi.org/10.1016/j.ijpe.2021.108250.

Praveen, U., Farnaz G., Ghasib H. (2019). Inventory management and cost reduction of supply chain processes using AI based time-series forecasting and ANN modeling, *Procedia Manufacturing*, Volume 38, 2019, Pages 256-263, ISSN 2351-9789, https://doi.org/10.1016/j.promfg.2020.01.034.

Priore, P., Ponte B., Rosillo R., and David de la Fuente. (2019). "Applying Machine Learning to the Dynamic Selection of Replenishment Policies in Fast-Changing Supply Chain Environments." *International Journal of Production Research* 57 (11): 3663–3677. https://www.tandfonline.com/doi/abs/10.1080/00207543.2018.1552369?journalCode=tprs20

Rajesh, R. (2020). *A grey-layered ANP based decision support model for analyzing strategies of resilience in electronic supply chains. Engineering Applications of Artificial Intelligence*, 87, Article 103338.

Raza, S. A., Govindaluri, S. M., & Bhutta, M. K. S. (2023). Research themes in machine learning applications in supply chain management using bibliometric analysis tools. Benchmarking: *An International Journal*, 30(3), 834–867. https://doi.org/10.1108/bij-12-2021-0755

Ren, C. Dong, J. Ding H. and Wang W., (2006). A SCOR-Based Framework for Supply Chain Performance Management,. *IEEE International Conference on Service Operations and Logistics, and Informatics*, Shanghai, China, 2006, pp. 1130-1135, doi: 10.1109/SOLI.2006.328909.

Riahi, Y., Saikouk, T., Gunasekaran, A., & Badraoui, I. (2021). Artificial intelligence applications in supply chain: A descriptive bibliometric analysis and future research directions. *Expert Systems With Applications*, 173, 114702. https://doi.org/10.1016/j.eswa.2021.114702

Richey, R. G., Chowdhury, S., Davis-Sramek, B., Giannakis, M., & Dwivedi, Y. K. (2023). Artificial intelligence in logistics and supply chain management: A primer and roadmap for research. *Journal of Business Logistics*, 44(4), 532–549. https://doi.org/10.1111/jbl.12364

Rodriguez, O., Chowdhury, S., Beltagui, A., & 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*, 58(15), 4610–4630. https://doi.org/10.1080/00207543.2020.1761565

Sandra L. and Bernd H., (2021). Applications of artificial intelligence in supply chain management: Identification of main research fields and greatest industry interests, ERCIS Working Paper, No. 37, Westfälische Wilhelms-Universität Münster, *European Research Center for Information Systems (ERCIS), Münster*

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

Sharma, R., Shishodia, A., Gunasekaran, A., Min, H., & Munim, Z. H. (2022). The role of artificial intelligence in supply chain management: mapping the territory. *International Journal of Production Research*, 60(24), 7527–7550. https://doi.org/10.1080/00207543.2022.2029611

Sharma, S., and Singh G. (2021). Intelligent Warehouse Stocking Using Machine Learning; Intelligent Warehouse Stocking Using Machine Learning. *2021 IEEE International Conference on Mobile Networks and Wireless Communications (ICMNWC)*. https://www.semanticscholar.org/paper/Intelligent-Warehouse-Stocking-Using-Machine-Puneet-Sharma/1c25c18073f06ac89a50a559dd336656c4c99d53

Shavaki, F. H., & Ghahnavieh, A. E. (2023). Applications of deep learning into supply chain management: a systematic literature review and a framework for future research. *Artificial Intelligence Review*. https://doi.org/10.1007/s10462-022-10289-z

Singh, R. K., Modgil, S., & Shore, A. (2023). Building artificial intelligence enabled resilient supply chain: a multi-method approach. *Journal of Enterprise Information Management*, 37(2), 414–436. https://doi.org/10.1108/jeim-09-2022-0326

Singh, S.P., Rawat, J., Mittal, M., Kumar, I., Bhatt, C. (2022). Application of AI in SCM or Supply Chain 4.0. In: Fernandes, S.L., Sharma, T.K. (eds) *Artificial Intelligence in Industrial Applications. Learning and Analytics in Intelligent Systems*, vol 25. Springer, Cham. https://doi.org/10.1007/978-3-030-85383-9_4

Sohrabi, M. (2023). *Artificial Intelligence in Logistic Industry. Implementation of Disruptive Technologies In Supply Chain Management*, 73–86. https://doi.org/10.59287/idtscm.70

Stewart, G. K. (1997). *Supply-chain operations reference model (SCOR): the first cross-industry framework for integrated supply-chain management. Logistics Information Management*, 10(2), 62–67. https://doi.org/10.1108/09576059710815716

Sun K., Roy A., Tobin J. M., (2024). Artificial intelligence and machine learning: Definition of terms and current concepts in critical care research, *Journal of Critical Care*, Volume 82, 154792, ISSN 0883-9441, https://doi.org/10.1016/j.jcrc.2024.154792

Tarasov, K. (2023). *Amazon's 100 drone deliveries puts Prime Air far behind Alphabet's Wing and Walmart partner Zipline. CNBC*. https://www.cnbc.com/2023/05/18/amazons-100-drone-deliveries-puts-prime-air-behind-google-and-walmart.html

The Economist (2017). *How Germany's Otto uses artificial intelligence. The Economist*. https://www.economist.com/business/2017/04/12/how-germanys-otto-uses-artificial-intelligence

Thomas, L. (2019*). Nike acquires A.I. platform Celect, hoping to better predict shopping behavior. CNBC*. https://www.cnbc.com/2019/08/06/nike-acquires-ai-platform-celect-hoping-to-predict-shopping-behavior.html

Timme, S.G. and Williams-Timme, C. (2003). *The real costs of holding inventory. Supply Chain Management Review*, V. 7, No. 4 (July/Aug. 2003), P. 30-37.

Tirkolaee, E. B., Saeid S., Farzaneh Mansoori Mooseloo, Hadi Rezaei Vandchali, and Samira Aeini. (2021). Application of Machine Learning in Supply Chain Management: A Comprehensive Overview of the Main Areas. *Mathematical Problems in Engineering 2021*: 1–14. https://doi.org/10.1155/2021/1476043.

Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research*, 122, 502–517. https://doi.org/10.1016/j.jbusres.2020.09.009

Tsolakis, N., Schumacher, R., Dora, M. (2022). *Artificial intelligence and blockchain implementation in supply chains: a pathway to sustainability and data monetisation?*. Ann Oper Res. https://doi.org/10.1007/s10479-022-04785-2

Unajan, M. C., Bobby D. Gerardo, and Ruji P. Medina. (2019). "A Modified Otsu-Based Image Segmentation Algorithm (OBISA)." *Lecture Notes in Engineering and Computer Science 2239* (1): 363–366.

Villalba-Diez, J., Schmidt D., Roman Gevers, Joaquín Ordieres-Meré, Martin Buchwitz, and Wanja Wellbrock. (2019). *Deep Learning for Industrial Computer Vision Quality Control in the Printing Industry 4.0. Sensors*. https://www.mdpi.com/1424-8220/19/18/3987

Wang Y, Meita Singgih, Jingyao Wang, Mihaela Rit (2019). Making sense of blockchain technology: How will it transform supply chains?, *International Journal of Production Economics*, https://doi.org/10.1016/j.ijpe.2019.02.002.

Wenzel, Hannah; Smit, Daniel; Sardesai, Saskia (2019). A literature review on machine learning in supply chain management, In: Kersten, Wolfgang Blecker, Thorsten Ringle, Christian M. (Ed.): Artificial Intelligence and Digital Transformation in Supply Chain Management: Innovative Approaches for Supply Chains. Proceedings of *the Hamburg International Conference of Logistics (HICL)*, Vol. 27, ISBN 978-3-7502-4947-9, epubli GmbH, Berlin, pp. 413-441, https://doi.org/10.15480/882.2478

Wood, C. (2021). *The self-driving race between Elon Musk's Tesla and Domino's pizza robots. CNBC*. https://www.cnbc.com/2021/07/10/self-driving-looking-less-like-elon-musk-more-dominos-pizza-robots.html

Yakubovskyi, R. & Morozov, Y. (2023). *Speech Models Training Technologies Comparison Using Word Error Rate, ACPS.*, Volume 8, Number 1, pp. 74 – 80, https://doi.org/10.23939/acps2023.01.074

Yao, Weiguo. (2018). Analysis on the Application of the Artificial Intelligence Neural Network on the New Energy Micro Grid. Proceedings of the 2017 *4th International Conference on Machinery, Materials and Computer (MACMC 2017)*. https://doi.org/10.2991/macmc-17.2018.144

Yarramalli S. S., Ponnam R. S. Manasa, Rao G. R. Koteswara, S. Fathimabi and P. Madasu, (2020). Digital Procurement on Systems Applications and Products (SAP) Cloud Solutions. Second International Conference on *Inventive Research in Computing Applications (ICIRCA)*, Coimbatore, India, 2020, pp. 473-477, doi: 10.1109/ICIRCA48905.2020.9183047.

Yosuke U, Hiromi M, Mitsuru T, Katsuhisa K, Tomohiro K, Yasushi H (2017). Warehouse Product Inspection System Achieves Work Efficiency and Quality Improvements : NEC Technical Journal | NEC. (n.d.). *NEC*. https://www.nec.com/en/global/techrep/journal/g17/n01/170108.html

Zdravković, M., Hervé Panetto, and Georg Weichhart. (2022). AI-Enabled Enterprise Information Systems for Manufacturing. *Enterprise Information Systems* 16 (4): 668–720. https://doi.org/10.1080/17517575.2021.1941275.

Zhao, X., Min Zhang, and Junjun Zhang (2021). Ensemble Learning-Based CNN for Textile Fabric Defects Classification. *International Journal of Clothing Science and Technology* 33 (4): 664–678. https://doi.org/10.1108/IJCST-122019-0188.

Zheng, Zibin & Dai, Hong-Ning. (2019). *Blockchain Intelligence: When Blockchain Meets Artificial Intelligence*. ARXIV. https://arxiv.org/abs/1912.06485

Zhou, G. and Gen, M., (1999). Genetic algorithm approach on multi-criteria minimum spanning tree problem. *European Journal of Operational Research*, 114, 141–152

Hoang Bao Pham is a PhD candidate at the Economics and Management program at Tomas Bata University's Department of Industrial Engineering and Information Systems, Faculty of Management and Economics. He has an MBA from the University of Bolton, United Kingdom. Email: pham_hoang@utb.cz

Petr Bris is Associate Professor at the Department of Industrial Engineering and Information Systems, Faculty of Management and Economics, Tomas Bata University. He has a PhD from the Technical University of Ostrava, Czech Republic and is holder of 8 patents and a member of the expert section of the Czech government office. Email: bris@utb.cz