Artificial intelligence in supply chain and operations management: a multiple case study research

Article *in* International Journal of Production Research · July 2023

DOI: 10.1080/00207543.2023.2232050

4 authors, including:

Violetta Giada Cannas
Carlo Cattaneo University LIUC

Maria pia Ciano
University of Nottingham

Mattia Saltalamacchia
Carlo Cattaneo University LIUC

International Journal of Production Research

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tprs20

Artificial intelligence in supply chain and operations management: a multiple case study research

Violetta Giada Cannas, Maria Pia Ciano, Mattia Saltalamacchia & Raffaele Secchi

INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH
https://doi.org/10.1080/00207543.2023.2232050

Taylor & Francis
Taylor & Francis Group

Artificial intelligence in supply chain and operations management: a multiple case study research

Violetta Giada Cannas[a], Maria Pia Ciano[b], Mattia Saltalamacchia[c] and Raffaele Secchi[c]

[a]School of Industrial Engineering, Carlo Cattaneo – LIUC University, Castellanza, Italy; [b]Nottingham University Business School, University of Nottingham, Nottingham, UK; [c]School of Economics and Management, Carlo Cattaneo – LIUC University, Castellanza, Italy

ABSTRACT

Artificial intelligence (AI) is increasingly considered a source of competitive advantage in operations and supply chain management (OSCM). However, many organisations still struggle to adopt it successfully and empirical studies providing clear indications are scarce in the literature. This research aims to shed light on how AI applications can support OSCM processes and to identify benefits and barriers to their implementation. To this end, it conducts a multiple case study with semi-structured interviews in six companies, totalling 17 implementation cases. The Supply Chain Operations Reference (SCOR) model guided the entire study and the analysis of the results by targeting specific processes. The results highlighted how AI methods in OSCM can increase the companies' competitiveness by reducing costs and lead times and improving service levels, quality, safety, and sustainability. However, they also identify barriers in the implementation of AI, such as ensuring data quality, lack of specific skills, need for high investments, lack of clarity on economic benefits and lack of experience in cost analysis for AI projects. Although the nature of the study is not suitable for wide generalisation, it offers clear guidance for practitioners facing AI dilemmas in specific SCOR processes and provides the basis for further future research.

ARTICLE HISTORY
Received 8 December 2022
Accepted 22 June 2023

KEYWORDS
Artificial intelligence; operations management; supply chain management; SCOR; industry 4.0; multiple-case study

1. Introduction

In recent years, artificial intelligence (AI) has assumed a prominent role in the Operations and Supply Chain Management (OSCM) literature. Indeed, AI has proven to be of great value to companies and is considered a key technology for Industry 4.0. It owes its popularity to its ability to make OSCM processes responsive to the various challenges that characterise today's world, such as unpredictable disruptions, dynamic customer expectations, intense global competition, increasingly strong and urgent pressure to digitalise companies, and ever-evolving technological innovations. (Fosso Wamba et al. 2021; Helo and Hao 2021; Zeba et al. 2020).

AI can be applied in several OSCM processes, such as order intake, supplier selection, quality control, production planning and control, smart connected products, services and maintenance, transportation, warehouse management, sales processes, and customer interfaces (see Table 1; Helo and Hao 2021). Furthermore, AI applications can support specific purposes, such as inventory management (Svoboda and Minner 2022), demand forecasting (Kantasa-ard et al. 2021), risk management (Baryannis et al. 2019; Wong et al. 2022), agility (Wong et al. 2022), resilience (Belhadi et al. 2022), and sustainability (Olan et al. 2022; Pournader et al. 2021). The common goals of these applications are reducing the time required for decision support, reducing human resources for repetitive tasks, and increasing capacity utilisation. (Helo and Hao 2021).

AI is commonly defined as a field of computer science that encompasses the development of systems that can perceive and interact with the environment in the form of text, video, audio, and more through approaches such as speech, vision, and natural language processing (NLP); that can learn from the experience provided by historical data through machine learning (ML) methods; and that can make decisions that normally require human intelligence through approaches such as planning, optimisation, simulation, modelling, programming, and expert systems (Helo and Hao 2021; Pournader et al. 2021).

Among the AI methods, ML techniques are considered the most applied in OSCM, and their applications have recently gained interest among researchers because of their capability to rapidly and intelligently manage big data and handle nonlinear problems that are widespread in real-world supply chains (Riahi et al. 2021;

CONTACT Maria Pia Ciano maria.ciano@nottingham.ac.uk Wollaton Rd, Lenton, Nottingham NG8 1BB, UK

Tirkolaee et al. 2021). This supports decision-making by exploiting both historical and real-time data with only minor human involvement (Zeba et al. 2020), improves performance (Fosso Wamba et al. 2021), and enhances competitive advantage (Dubey et al. 2020).

Notwithstanding the relevance of AI for OSCM, there is still little research on the role of AI in this field, and expertise on this subject is still limited (Helo and Hao 2021). As a result, nowadays, companies struggle to implement AI in their OSCM processes and face numerous barriers. Many companies have failed to fully comprehend the potential of AI (Pournader et al. 2021). Many companies lack a clear strategy, solid technology infrastructure, and the full commitment of top p management and are discouraged by the high expenditure required to build skills and acquire technology (Dubey et al. 2020; Helo and Hao 2021). A cause of the lack of clear direction, trust, and motivation for a conscious transition to AI may be found in the scarcity of empirical studies in the literature on AI to support OSCM processes, and the lack of examples of companies that have already implemented AI in OSCM. This certainly precludes obtaining insights and practical guidance on approaching the subject. Moreover, recent literature reviews on AI in OSCM underlined that the number of studies dedicated to the applications of ML algorithms in managing a supply chain is inadequate (Tirkolaee et al. 2021) and highlighted the need to analyse practical challenges and propose models to fit AI in operational environments to solve problems (Dhamija and Bag 2020).

Therefore, the current context demonstrates the need to further investigate the applications of AI in OSCM through more experience and insights from in-depth case studies in industry (Fosso Wamba et al. 2021; Pournader et al. 2021). To fill this gap, the present study aims to answer the following research questions (RQs) by empirically analysing multiple case studies:

RQ1. How do AI applications support supply chain and operations management processes?

RQ2. What are the benefits achieved by companies when using AI to support supply chain and operations management?

RQ3. What are the barriers tackled by companies when implementing AI to support supply chain and operations management?

By answering these questions, this study contributes to the advancement of theory and practice. Through the empirical analysis of case studies, the authors can report on real-life applications of AI in support of OSCM, identify the benefits obtained through these applications, and classify the barriers faced during their implementation.

The remainder of the article is organised as follows. Section 2 reports a literature review regarding the use of AI in OSCM processes organised according to the supply chain operations reference (SCOR) model, which is used as a reference model throughout the article. Section 3 describes the methodology by which this research was conducted, that is, multiple case studies, and outlines the cases considered and the steps followed for data collection and analysis. The results and analysis are presented in Section 4. Section 5 discusses the research questions. Finally, the limitations of this study, its implications, and future research directions are discussed in Section 6.

2. Literature review

The review of the existing literature has identified several applications of AI methods in OSCM. The results were classified following the SCOR model, as proposed by other recent studies (Chehbi-Gamoura et al. 2020), focusing on five core processes: 'plan', 'source', 'make', 'deliver', and 'return'.

The survey of the literature consisted of keywords searching through Scopus database (www.scopus.com) and was conducted in March 2023. Given the broad scope of the research, which addresses the application of AI to the five core processes of the SCOR model, we limited the literature survey to articles that included, in their title, keywords that expressly denote the area of investigation. Also, we refined the results by applying exclusion criteria that limited the search to English language articles, published by peer-reviewed journals, related to the subject area of 'Business, management and accounting'. The final query used for Scopus searching was the following:

(TITLE ('**artificial intelligence**') OR TITLE ('**AI**') AND TITLE ('**plan***') OR TITLE ('**sourc***') OR TITLE ('**mak***') OR TITLE ('**deliver***') OR TITLE ('**return***')) AND (LIMIT-TO (**SRCTYPE, 'j'**)) AND (LIMIT-TO (**SUBJAREA, 'BUSI'**)) AND (LIMIT-TO (**LANGUAGE, 'English'**))

Then, from the resulting list of documents, we screened titles, abstracts, and full text to exclude papers that were not related to the main scope of this study, and we conducted 'snowballing' through their reference list to include additional papers that contributed to the main scope of the study. This procedure resulted in an association of the AI methods with the SCOR processes, with details of the application of these methods and the benefits achieved through it. The authors then analysed the literature related to the main barriers tackled by companies when implementing AI to support OSCM. The main results are summarised in Table 1.

2.1. Plan

The Plan processes include 'gathering of requirements, gathering of information on available resources, balancing requirements and resources to determine planned capabilities and gaps in demand or resources, and identifying actions to correct these gaps' (APICS 2017). The literature investigates AI in planning processes, mostly in the domains of demand forecasting, demand planning, and inventory management.

As far as demand forecasting and planning are concerned, datasets related to demand, in most real-world problems, are nonlinear, complex, and have ambiguous structures and patterns. This can disturb forecasting accuracy, which is fundamental for ensuring the quality of managerial decision-making. To address this issue, the literature proposes AI methods based on ML as effective methods when adequate data are available. In the energy industry, Tutun et al. (2022) proposed AI for forecasting electricity consumption through cohort intelligence & adaptive neural fuzzy inference system, and Khashei and Chahkoutahi (2021) proposed AI for electricity demand forecasting through fuzzy hybrid intelligence based seasonal models. In these cases, ML methods learn from data and adapt without requiring much information, thus ensuring generalisability and flexibility. In the food industry, Priyadarshi et al. (2019) show that ML, and in particular, long short-term memory (LSTM) and support vector regression (SVR), applied to demand forecasting at retail stage for selected vegetables increases performance in terms of inventory turnover and days of stock coverage to prevent potential stockouts and decrease the bullwhip effect. The benefits derived from ML methods are the reduction of forecast error and days of coverage, growth of the inventory turnover index, and reduction in the number of days out of stock. However, the ML methods have certain limitations. First, they require a large amount of historical data to reach the desired accuracy; patterns in the underlying data are also not considered; and finally, they do not have a very good performance in dealing with ambiguities and uncertainties (Khashei and Chahkoutahi 2021). To overcome these limitations, the use of hybrid methods, such as an adaptive neural-based fuzzy inference system (ANFIS) and fuzzy seasonal multilayer perceptron (FSMLP), which combine statistical, metaheuristic, and ML approaches, is proposed. Different applications of these algorithms can be used to forecast energy demand (Khashei and Chahkoutahi 2021; Singh and Challa 2016; Tutun et al. 2022).

In addition, ML determines the best inventory management policy to obtain optimal inventory control and supply chain configuration with minimum cost in the context of 'intermittent demand products', or spare parts (Cantini et al. 2022; Priore et al. 2019). Aktepe, Yanık, and Ersöz (2021) underlined the success of ML applications, artificial neural network and support vector regression, for the demand and inventory management of spare parts in the construction industry, which is considered a complex matter because of the high number of parts managed and the risk of stock obsolescence, intermittent demand, and high responsiveness required. Lolli et al. (2019) proposed ML, support vector machines with a Gaussian kernel and deep neural networks, for forecasting and stock control of intermittent demand. Selecting the best inventory management policy, achieving an average accuracy of 88% and reducing operating costs proved to be a major benefit of the proposed methods.

2.2. Source

The source processes include 'issuing purchase orders, scheduling deliveries, receiving orders, validating orders, storing goods, and accepting suppliers' invoices' (APICS 2017). The literature investigates the use of AI in source processes in the domains of supplier selection and verification of incoming order quality.

Supplier selection is one of the most crucial stages of sourcing, because of the important upstream role of suppliers in terms of time, cost, and quality. Most studies on this topic have used a combination of fuzzy set theory and multi-criteria decision models (MCDM) for supplier selection to address the vagueness of information on supplier attributes and the conflicting objectives of identifying suppliers that are both reliable and cost-effective (Sharma et al. 2022).

According to Riahi et al. (2021), other popular techniques include artificial neural network (ANN) and genetic algorithms. An interesting aspect of ANN concerns the increasing focus on green supplier selection or supplier selection in the health sector (e.g. Bahadori et al. 2020; Fashoto et al. 2016). Most studies adopting artificial neural network (ANN) combine several techniques. For example, Kuo, Wang, and Tien (2010) combined an ANN with data envelopment analysis (DEA) and a network analytic process (ANP) to select the best green supplier and evaluated the model to a case company operating in the electronic industry. Bahadori et al. (2020) proposed a supplier selection model for hospitals to identify the best medical equipment supplier using a combination of ANN and fuzzy VIKOR. Regarding genetic algorithms, among the many studies, Fallahpour et al. (2017) proposed a new genetic-based intelligent approach, gene expression programming (GEP), to improve the supplier selection process and overcome other AI methods' drawback of being a black box system; indeed, the GEP method provides an explicit mathematical model for supplier performance based on the determined criteria and can provide a fast evaluation of potential new suppliers. This study evaluated the method through a case study in the garment industry by applying three accuracy measures criteria, including MSE, RMSE, and MAE, and found that the GEP based model performs better than ANN integrated model. Luan et al. (2019) presented a hybrid method based on a genetic algorithm and ant colony optimisation to combine the advantages of the former, namely, high initial speed-up convergence, and the merits of the latter, namely, parallelism and effective feedback. The method was tested via a simulation case referring to extant literature, without using specific case studies. Green supplier selection, as an increasingly topical theme, is also addressed by methods based on genetic algorithms (Hamdan and Jarndal 2017; Yeh and Chuang 2011; Zhang and Cui 2019).

According to Tirkolaee et al. (2021), among ML techniques, the literature on supplier selection problems presents both supervised learning and reinforcement learning techniques. In the former, the studies focus on the combination of decision trees and support vector machines (SVM), and in the latter, on the Q-learning technique. In particular, the authors reported the key study by Guo, Yuan, and Tian (2009) based on potential SVM and decision trees as the main reference for the procedure to follow and for demonstrating that, compared to traditional MDCM and original SPV methods, it reduces the number of binary classifiers, increases the accuracy and decreases the computation time in different classifications, and selects the most 'informative' features to develop classifiers. Instead, Islam, Amin, and Wardley (2021) adopted a relational regressor chain method to determine future demand and used it to feed a multi-objective programming model to identify suitable suppliers and order quantities from each supplier.

Verification of the quality of incoming orders in the literature is addressed by learning techniques. In general, these techniques can be applied at all quality control stages. Mani et al. (2021) considered an incoming inspection problem as a reinforcement-learning task. They developed a temporal difference learning approach to predict the acceptance and rejection paths of raw materials by analysing different paths that the raw materials could travel. The method was tested by using Original Equipment Manufacturers (OEM) Incoming Inspection process as case study. Zhao, Zhang, and Zhang (2021) applied an ANN-based technique, specifically based on the convolutional neural network (CNN), in a visual recognition system for the identification and classification of different types of defects in the textile industry, achieving an accuracy rate of 97.8%. Unajan, Gerardo, and Medina (2019) applied deep learning (DL) in machine vision systems, originally using Otsu's algorithm in conjunction with the OBISA algorithm, for identifying product scraps, achieving an accuracy rate of 85.11%.

2.3. Make

The make processes include 'processing, maintenance, repair, overhaul, recycling, refurbishment, manufacturing and other common types of material-conversion processes' (APICS 2017). The literature investigates the use of AI in the make processes, regarding scheduling, manufacturing, quality, and maintenance.

The literature shows that ANN-based techniques are employed in scheduling problems to determine the optimal paths of re-entrant products, while the simulated annealing algorithm finds application in the prediction of machine failures in order to reduce repair costs (Kim and Kim 2021; Wu et al. 2020). Fuzzy logic (FL) can be applied to software for defining the best job shop flow, allowing a reduction in the production cycle time (Chan, Prakash, and Mishra 2013; Mohapatra, Benyoucef, and Tiwari 2013). An alternative may be genetic algorithms, also adopted in software for defining the best flow in production scheduling problems (Lei 2010). ML can also help to better plan customisation needs. For example, Chen, Tai, and Hung (2012) applied NNs to group similar customisation needs. They then used existing inventory information to select parts for production, which dramatically reduced the cost throughout the supply chain compared to a human decision.

Since the beginnings of smart manufacturing and Industry 4.0 concepts, the literature linking production and AI techniques has focused heavily on the advantage that real-time data obtained through IoTs and sensors can bring for controlled and self-regulated production (Lăzăroiu, Kliestik, and Novak 2021; Lee et al. 2018). For example, the optimisation of energy and resource utilisation in production can be done using the k-means algorithm that creates reliable and updated data on their real-time monitoring (Manimuthu et al. 2021; Omwando et al. 2018). Wuest, Irgens, and Thoben (2014) proposed an approach to increase the process and product quality in manufacturing by monitoring data based on product status and using a combination of SVM and cluster analysis.

Along with production control and monitoring, there is the topic of quality. Product testing and fault detection in the process or intermediate outputs are fundamental to avoid jeopardising the quality of the product and the safety and efficiency of the process. Many studies have focused on visual inspection. For instance, Villalba-Diez et al. (2019) improved the defect detection performance during the process of producing gravure cylinders, reduced quality inspection costs by process automation, and developed a deep neural network (DNN) soft sensor that compares a scanned surface to the used engraving file, achieving an automated classification accuracy rate of 98.4%. Also, Sharma (2023) used the digital twin method to design, simulate, and validate an automated battery module inspection system that uses cobots and machine vision to inspect electric vehicle batteries for defects. The simulation results shown that this automated inspection can reduce time and increase accuracy of inspection, if compared to human checking.

Fault detection opens the topic of maintenance, particularly predictive maintenance. Predictive maintenance primarily involves applications of techniques based on ML (Carvalho et al. 2019; Kumar and Hati 2021). For instance, Luo et al. (2019) developed a deep learning model to automatically select impulse responses from vibration signals during long-term operations to enable early fault detection under time-varying conditions. Encapera, Gosavi, and Murray (2021) described the use of Reinforcement Learning to solve large-scale Markov11 decision processes for total productive maintenance and quicken optimisation. Kaparthi and Bumblauskas (2020) described the application of an algorithm based on a tree model to predict machine failures using data from the cloud. This results in greater customer satisfaction as they can thus have a better after-sale maintenance service.

Despite the several benefits of AI techniques in the Make processes, Lee et al. (2018) stated that a possible challenge is that AI techniques require massive and clean datasets with minimum biases. For example, in visual inspection, some processes may be of such a nature that each new product implies that the DNN model has not been previously confronted with these images. Therefore, the training and testing of DNN is a real challenge (Villalba-Diez et al. 2019).

2.4. Deliver

The delivery processes include 'receiving, validating, and creating customer orders, scheduling order deliveries, picking, packing and shipping, and invoicing customers' (APICS 2017). The use of AI in delivery processes has been investigated in the literature, in the domains of stocking, process enquiry and quote, shipping, picking, and logistics optimisation.

Regarding stocking, Priore et al. (2019) adopted inductive learning to determine the best procurement policy, achieving 88% accuracy and reducing operating costs. Sharma and Singh (2021) proposed intelligent warehouse stocking using linear regression, random forest, and XGBoost for predicting the demand and a visual representation of the results of stocking to better understand how to avoid excessive overstocks.

Regarding process enquiry and quote, NLP implemented in chatbots can be used to answer generic customer enquiries and even to automate direct sales (Toorajipour et al. 2021; Zdravković, Panetto, and Weichhart 2022). These virtual assistants can be extremely effective for the automation of customer service enquiries, as they can personalise communication with customers by detecting their personalities and adapting to them (Shumanov and Johnson 2021). FL can enable timely pricing to complete quotes for customers (Leung et al. 2019). This resulted in a reduction of the average planning time of offers by 60% and an increase in the acceptance rate of quotes by 78%. The artificial bee colony algorithm can be applied to an automated system that can execute simultaneous quotes by matching the various strategies of sellers. In comparison to any other solution, this increases the number of quotes by up to 99%, which leads to a deal and increases the average buyer's utility by up to 80% (Kolomvatsos et al. 2016).

Literature reports the use of genetic algorithms applied through data mining also in support of shipping, as it can optimise product delivery methods and logistics in general. This application showed a reduction in distribution costs and delivery times, achieving an average customer satisfaction of 98.75% (Li and Xiao 2021).

Regarding picking, Nowak, Hewitt, and White (2012) proposed the application of tree models to determine which use of loads could reduce the total cost of transport, achieving an average reduction of 5%, which could reach 8% for the largest loads.

Studies can be found in the literature using ANN-based techniques and genetic algorithms for logistics optimisation. Among the applications of ANN are tools for the recognition and analysis of identification codes and tags in pallets. These tools make it possible to optimise warehouse layout, improve the storage of raw materials, reduce procurement times, and reduce transport time and costs (Ellefsen et al. 2019). Moreover, an ANN-based decision support system can plan the best truck route. This leads to the reduction of workloads through adaptive routing of trucks and the reduction of their waiting times (Hill, Jü, and Böse 2016). Other applications can be found in driver assistance systems for freight vehicles. They enable greater efficiency, both in shipping through the creation of better routes and in systems through predictive maintenance (Loske and Klumpp 2021).

Furthermore, Dosdoğru, Boru İpek, and Göçken (2021) suggested the use of genetic algorithms-based decision support systems to precisely set the lead time and define the delivery route, thus reducing transportation costs.

2.5. Return

The return process includes 'activities associated with the reverse flow of goods. The processes associated with moving material from a customer back through the supply chain to address product defects, ordering, or manufacturing, or to perform upkeep activities' (APICS 2017). For this reason, the application of AI to the return process has been related to the concept of the circular economy (CE) and in particular, the CE component of reverse logistics (Dhamija and Bag 2020; Li, Liu, and Li 2019; Naz et al. 2022). Recent studies on reverse logistics have started focusing on the development of AI models to optimise environmental factors, and machine learning algorithms have been proposed in the literature to support CE (Noman et al. 2022). Indeed, reverse logistics are considered more complex to manage than forward logistics because many factors are unknown, such as the volumes, quality, and timing of product returns (Birkel and Müller 2021).

According to a recent review published by Wilson, Paschen, and Pitt (2021), reverse logistics can be conceptualised in four main domains to which AI can contribute: (i) network design, by evaluating potential third-party logistics (3PL) providers and defining the optimal number and location of collection points; (ii) collection, by solving complex routing problems, estimating the number of articles returned during collection, and supporting the gatekeeping function; (iii) warehousing, by forecasting return volumes and improving decision support for inventory management and supporting, sorting, and inspection tasks; and (iv) processing, by selecting the most favourable processing option based on numerous qualitative and quantitative factors.

The literature underlines the capability of AI for CE and reverse logistics to provide more quantitative and robust solutions than other methods (Wilson, Paschen, and Pitt 2021). In addition, AI in reverse logistics can improve network design and collection by reducing inventory carrying and holding costs without increasing location costs and customer service, automating returns sorting and making it faster, and increasing the environmental sustainability of processing options (Dutta et al. 2021).

2.6. Barriers to AI implementation in OSCM

Literature on barriers to the successful implementation of AI in OSCM is limited and related to technical issues related to the development of specific algorithms. For example, there is a need for a massive amount of clean data to train and test the models (Lee et al. 2018; Villalba-Diez et al. 2019) and the need to apply complex hybrid methods to deal with ambiguities and uncertainties typical of real data (Khashei and Chahkoutahi 2021). However, to the best of the authors' knowledge, there is a scarcity of contributions related to all issues that hinder AI implementation within real companies, which should include not only technical but also financial and organisational barriers. Therefore, it is useful to broaden this analysis to the vast and consolidated body of literature on the implementation of Industry 4.0. Indeed, the barriers identified as critical by previous literature for the implementation of Industry 4.0 technologies can also be critical for AI, which is included among the plurality of core technologies encompassed by Industry 4.0 (Bai et al. 2020; Benitez, Ayala, and Frank 2020; Frank, Dalenogare, and Ayala 2019; Kamble et al. 2020; Osterrieder, Budde, and Friedli 2020). Thus, the analysis of barriers related to the implementation of Industry 4.0 could be considered a good starting point for the empirical study of barriers to AI implementation. The main results are summarised in Table 2.

A recent study by Agostini and Filippini (2019) analysed the organisational and managerial challenges to Industry 4.0 adoption faced by Italian manufacturing firms through a survey research. They found that organising for Industry 4.0 requires training and continuous professional development of employees, lean production practices and continuous improvement approaches in production processes, the existence of a modern ICT infrastructure, and integration and collaboration among supply chain partners increasing openness and adaptability. In addition, Pasi, Mahajan, and Rane (2020) conducted a literature review on IoT in supply chain management and underlined that the challenges to smart supply chain management are technology selection, data management, cyber security, cultural resistance and structural problems. Also, Raj et al. (2020) studied barriers inhibiting the adoption of Industry 4.0 based on a literature review and expert input. In total, 15 barriers were identified, and the results highlighted how the impacts of these barriers are different in developed and developing economies. The most important barrier for developing economies was the lack of standards, regulations, and forms, and the low maturity level of the desired technology for developed economies. However, the lack of a digital strategy, alongside resource scarcity, has emerged as the most prominent barrier in both developed and developing economies.

The following studies deepened the analysis of these barriers. Kumar, Vrat, and Shankar (2021) categorised, based on a literature analysis and expert input, 23 barriers to Industry 4.0 implementation. Stentoft et al. (2021) categorised ten barriers to Industry 4.0 implementation and empirically analysed the implementation of Industry 4.0 in small-medium enterprises (SMEs) through survey and case research. Among them, the barriers most acknowledged by the companies analysed resulted in a lack of understanding of the strategic importance of Industry 4.0, lack of employee knowledge about Industry 4.0, too much focus on operations at the expense of development, and lack of employee readiness. Moreover, Majumdar, Garg, and Jain (2021) focused on the study of barriers to Industry 4.0 implementation in SMEs in the textile and clothing industry. The study started with 22 barriers identified in the literature and identified four driving barriers in the industry and textile context: lack of awareness and commitment of top management, lack of trained personnel, lack of government support and policies and incentives for Industry 4.0, insufficient research and development in Industry 4.0. Chauhan, Singh, and Luthra (2021) categorised 20 barriers to Industry 4.0, and studied how they influence the linkage between digitalisation and the firm's performance in the emerging economy context of India through survey research. Their results indicate that Industry 4.0 adoption is dependent on extrinsic barriers such as resistance by other stakeholders, lack of standard architecture, lack of Internet access, contractual and privacy and security issues, and regulatory underdevelopment. In the context of manufacturing companies in India, Nimawat and Gidwani (2021) explored the barriers relevant to Industry 4.0, identifying 15 barriers from the literature, and analysed their causal relationships using the DEMATEL technique, finding that the implementation cost has the maximum effect on all the other barriers. In the context of Italian manufacturing companies, Pozzi, Rossi, and Secchi (2021) analysed the factors affecting the implementation of Industry 4.0 through case research. Their results underlined the importance of continuous improvement/lean culture, explicit objective recognition, top management project leadership, multifunctional project teams, clear and defined project plans, and formal and specific training programmes for the successful implementation of Industry 4.0. Finally, another recent study in Italy was performed by Cugno, Castagnoli, and Büchi (2021), who identified prominent barriers to Industry 4.0 implementation through in-depth interviews and multiple case studies. They categorised 11 barriers from the literature analysis, and their results highlighted four main barriers related to knowledge issues, economic-financial resources, cultural aspects, and system conditions.

2.7. Summary of the results

From the analysis of the literature, various applications of AI techniques related to the five processes of the SCOR model and interesting benefits for companies have been underlined as a result of these applications. Table 1 shows a synthesis of the results obtained from the literature review on AI applications for the different SCOR processes and the benefits achieved by companies owing to these AI applications. In particular, the literature review shows that the main difference in the specific AI applications, identified in research studies, is related to the context were the solutions proposed are applied. In the plan process, AI solutions have been used for demand forecasting in the energy and food industry, and for inventory management the case of intermittent demand products and spare parts. In the source process, AI solutions have been used for supplier selection in the electronic and garment industry, and in the health sector, and for quality control of incoming orders in OEM and textile industry. In the make process, AI solutions have been used for scheduling, manufacturing, quality and maintenance in manufacturing and production industry, and scheduling in the technology industry. In the deliver process, AI solutions have been used for stocking, picking, shipping and process inquiry and quote in the warehousing and logistics industry, for process inquiry and quote in electronic industry and logistic optimisation in agriculture industry. In the return process, AI solutions have been used for network design, optimisation of collection activities, optimisation of warehousing and processing selection in logistics industry focusing on reverse logistics.

The literature on barriers to AI implementation has not been covered by recent studies, and only a few technical barriers related to the development of specific ML algorithms have been identified. Thus, this study analysed the literature on barriers related to the implementation of Industry 4.0, which includes AI among its technologies. Table 2 categorises and lists all the barriers identified in the literature related to the implementation of Industry 4.0.

2.8. Research gaps, problem statement and research objectives

This study is driven by the research gaps emerged from the review of the literature presented in the previous sections, which, in line with recent studies on AI in OSCM (Cadden et al. 2022; Dhamija and Bag 2020; Pournader et al. 2021; Sharma et al. 2022; Tirkolaee et al. 2021), can be synthetised as follows.

Table 1. Summary of the literature review on AI applications and benefits.

SCOR Processes	Specific AI application in OSCM	Generic AI application in OSCM	Benefits	References
Plan	• Energy industry: forecasting of electricity consumption through cohort intelligence & adaptive neural fuzzy inference system; electricity demand forecasting through fuzzy hybrid intelligence-based seasonal models; electricity demand forecasting through hybrid methods, such as adaptive neural-based fuzzy inference system (ANFIS) and fuzzy seasonal multilayer perceptron (FSMLP) • Food industry: demand forecasting at the retail stage for selected vegetables through long short-term memory (LSTM) and support vector regression (SVR). • Intermittent demand products / spare parts industry: demand and inventory management of spare parts through artificial neural network (ANN) and SVR.	• Demand forecasting and planning • Inventory management	• Growth of inventory turnover index • Reduction of the number of days out of stock • Optimal inventory control	Singh and Challa 2016; Khashei and Chahkoutahi 2021; Tutun et al. 2022; Bala 2012; Priyadarshi et al. 2019; Aktepe, Yanık, and Ersöz 2021; Lolli et al. 2019; Priore et al. 2019; Cantini et al. 2022
Source	• Electronic industry: green supplier selection through ANN with data envelopment analysis (DEA) and a network analytic process (ANP); • Health sector: identify the best medical equipment supplier using a combination of ANN and fuzzy VIKOR; • Garment industry: supplier selection through a genetic-based intelligent approach, gene expression programming (GEP); • Original Equipment Manufacturers: temporal difference learning approach to predict the acceptance and rejection paths of raw materials; • Textile industry: identify and classify different types of defects through a convolutional neural network (CNN)	• Supplier selection • Quality control of incoming orders	• Increase of the accuracy and decrease of the computation time in different classifications for supplier selection • High accuracy in defects identification	Sharma et al. 2022; Riahi et al. 2021; Kuo, Wang, and Tien 2010; Gegovska, Köker, and Çakar 2020; Fashoto et al. 2016; Bahadori et al. 2020; Fallahpour et al. 2017; Luan et al. 2019; Yeh and Chuang 2011; Hamdan and Jarndal 2017; Zhang and Cui 2019; Guo, Yuan, and Tian 2009; Islam, Amin, and Wardley 2021; Mani et al. 2021; Zhao, Zhang, and Zhang 2021; Unajan, Gerardo, and Medina 2019
Make	• Manufacturing and production industry: forecasted machine breakdown using simulated annealing (SA) algorithm combined with a fuzzy logic controller; dynamic dispatching of re-entrant production through deep neural network (DNN) and Markov decision processes (MDP); allocations of the machines based on the priority with artificial immune system (AIS) combined with a fuzzy logic controller (FLC); reduction in the production cycle time through artificial immune system (AIS); define the best flow in a flexible job shop with decomposition-integration genetic algorithm (DIGA); combination of IoTs and sensors can bring for controlled and self-regulated production; real-time monitoring and optimisation of resources and energy using k-means algorithm; increase the accuracy and reduce the cost of an industrial visual inspection through deep neural network (DNN) soft sensor; in predictive maintenance the use of machine learning technics avoids unnecessary replacement of equipment, saves costs and improves the safety, availability and efficiency of processes. • Tecnology industry: grouping products with the similar customised using neural network;	Scheduling Manufacturing Quality Maintenance	Reduction of costs Optimisations of resources usage (for instance, energy) Improved early fault detection Improved afters-sales maintenance service	Kim and Kim 2021; Wu et al. 2020; Chan, Prakash, and Mishra 2013; Mohapatra, Benyoucef, and Tiwari 2013; Chen, Tai, and Hung 2012; Lee et al. 2018; Lăzăroiu, Kliestik, and Novak 2021; Manimuthu et al. 2021; Omwando et al. 2018; Wuest, Irgens, and Thoben 2014; Carvalho et al. 2019; Kumar and Hati 2021; Luo et al. 2019; Encapera, Gosavi, and Murray 2021; Kaparthi and Bumblauskas 2020; Lee et al. 2018; Villalba-Diez et al. 2019.

(*continued*)

Table 1. Continued.

SCOR Processes	Specific AI application in OSCM	Generic AI application in OSCM	Benefits	References
Deliver	• Warehousing and logistics industry: determine the best procurement policy reacting to environmental changes by adopting an inductive learning algorithm; predicting the demand and intelligent warehouse stocking using linear regression, random forest, and XGBoost; answer generic customer enquiries and even automate direct sales with natural language processing (NLP); a B2B flexible pricing decision support system applying fuzzy logic technique; optimisation of the splitting loads with tree models; • Electronic industry: automated concurrent negotiations capable of performing simultaneous quotations through artificial bee colony algorithm; • Agriculture industry: optimise logistics and product delivery methods using genetic algorithms applied through data mining.	• Stocking • Process inquiry and quote • Shipping • Picking • Logistics optimisation	• Reduction of offer planning time • Effective communication with the customer • Increase in offers acceptance • Increase in customer satisfaction • Reduction of transportation time and costs	Priore et al. 2019; Sharma and Singh 2021; Leung et al. 2019; Kolomvatsos et al. 2016; Li and Xiao 2021; Nowak, Hewitt, and White 2012; Ellefsen et al. 2019; Hill, Jü, and Böse 2016; Loske and Klumpp 2021; Dosdoğru, Boru İpek, and Göçken 2021; Shumanov and Johnson 2021; Toorajipour et al. 2021; Zdravković, Panetto, and Weichhart 2022
Return	• Logistics industry: optimise the location selection in the remanufacturing logistics network through ant colony optimisation (MACO) algorithm; support reverse logistics in circular economy with fuzzy logic and decision support system; ML technique in the reverse logistics can contribute to evaluating potential third-party logistics, solving complex routing problems, forecasting return quantities, selecting the most appealing processing option; improve network design and collection using genetic algorithm.	• Network design • Optimisation of collection activities • Optimisation of warehousing • Processing selection	• Reduction of inventory carrying and holding costs • Reduction of location costs • Improvement of customer service • Automation and speed up of returns sorting • Increased environmental sustainability	Li, Liu, and Li 2019; Dhamija and Bag 2020; Naz et al. 2022; Noman et al. 2022; Birkel and Müller 2021; Wilson, Paschen, and Pitt 2021; Dutta et al. 2021

There is a scarcity of studies in the literature addressing the way how organisations should implement AI techniques for supporting OSCM processes. Few models have been proposed to guide companies that want to implement and use AI to support OSCM processes.

There is a lack of exploratory empirical in-depth studies that proposed AI techniques to support OSCM processes, such as multiple case studies research. Most studies addressed this topic through not empirical methods, performing bibliometric or systematic literature reviews, or testing new AI applications with simulated data.

There is a dearth of evidence from mature industrial applications and the generalisability of the AI techniques proposed is not assessed today. Most studies that applied AI solutions to real cases addressed single experimental cases, focusing on a single application to a single sector.

In addition, this study based its analysis also considering the results obtained from recent literature review studies on AI applied to different OSCM processes, which highlighted and confirmed similar issues. For example, Abbas Naqvi and Amin (2021), after reviewing 92 papers related to supplier selection, mentions the possibility that advanced deep learning (DL) and ML techniques can be applied to forecast the parameters of the optimisation models only in future research. Islam, Amin, and Wardley (2021) highlighted that before their study, no other studies considered ML methods in supplier selection along with the problem of order allocation holistically. Furthermore, the literature review on AI, ML, and DL in smart logistics by Woschank, Rauch, and Zsifkovits (2020) underlines that most studies in the field are either conceptual, in a very early testing phase, or laboratory experiments.

In line with the abovementioned research gaps, we can conclude that the problem addressed by this research is the lack of empirical studies in the literature that analyse in-depth industry case experience with AI. The consequence is that it is difficult for practitioners to find guidelines to implement AI within different industrial realities and understand the applicability of AI techniques to OSCM. Therefore, this study conducts empirical qualitative research through multiple case studies, aiming to achieve the following objectives: (i) Understand how AI applications support OSCM; (ii) Comprehend what are the benefits achieved by companies when using AI to support OSCM; (iii) Acquire what are the barriers tackled by companies when implementing AI to support OSCM.

3. Methodology

This study addresses the research gaps and answers the research questions by combining the findings of the

Table 2. Summary of the literature review on barriers to Industry 4.0 implementation.

Category	ID	Barriers	Reference
Financial barriers	1	High investment needed to implement Industry 4.0 initiatives, insufficient financial resources within the company and scarcity of external financing	Raj et al. 2020; Kumar, Vrat, and Shankar 2021; Stentoft et al. 2021; Majumdar, Garg, and Jain 2021; Chauhan, Singh, and Luthra 2021; Cugno, Castagnoli, and Büchi 2021; Nimawat and Gidwani 2021
	2	Lack of clarity regarding the economic benefit and low experience in budgeting, cost analysis, resource allocation, etc. for Industry 4.0	Raj et al. 2020; Kumar, Vrat, and Shankar 2021; Majumdar, Garg, and Jain 2021; Chauhan, Singh, and Luthra 2021; Cugno, Castagnoli, and Büchi 2021; Nimawat and Gidwani 2021
	3	Lack of risk management tools to decide the amount of investments in Industry 4.0	Majumdar, Garg, and Jain 2021
Organisational barriers	4	Enhanced skills required for employees, shortage of workforce with adequate skillset in the labour market and lack of internal training	Raj et al. 2020; Agostini and Filippini 2019; Kumar, Vrat, and Shankar 2021; Stentoft et al. 2021; Majumdar, Garg, and Jain 2021; Chauhan, Singh, and Luthra 2021; Cugno, Castagnoli, and Büchi 2021; Nimawat and Gidwani 2021; Pozzi, Rossi, and Secchi 2021
	5	Lack of internal digital culture and training to embrace technological advancements	Raj et al. 2020; Agostini and Filippini 2019; Kumar, Vrat, and Shankar 2021; Stentoft et al. 2021; Majumdar, Garg, and Jain 2021; Chauhan, Singh, and Luthra 2021; Cugno, Castagnoli, and Büchi 2021; Nimawat and Gidwani 2021
	6	Lack of employees' readiness and high resistance to change	Raj et al. 2020; Kumar, Vrat, and Shankar 2021; Stentoft et al. 2021; Chauhan, Singh, and Luthra 2021; Cugno, Castagnoli, and Büchi 2021; Pasi, Mahajan, and Rane (2020)
	7	Lack of knowledge management systems and low integration and collaboration among organisation departments and supply chain partners	Raj et al. 2020; Agostini and Filippini 2019; Majumdar, Garg, and Jain 2021; Chauhan, Singh, and Luthra 2021; Pozzi, Rossi, and Secchi 2021; Pasi, Mahajan, and Rane (2020)
Strategical barriers	8	Difficult process changes and ineffective change management	Raj et al. 2020; Majumdar, Garg, and Jain 2021; Chauhan, Singh, and Luthra 2021; Nimawat and Gidwani 2021; Pozzi, Rossi, and Secchi 2021
	9	Lack of strategical roadmap for Industry 4.0 and weak methodical approach for implementation	Raj et al. 2020; Kumar, Vrat, and Shankar 2021; Majumdar, Garg, and Jain 2021; Chauhan, Singh, and Luthra 2021; Nimawat and Gidwani 2021; Pozzi, Rossi, and Secchi 2021
	10	Lack of top management commitment	Kumar, Vrat, and Shankar 2021; Stentoft et al. 2021; Chauhan, Singh, and Luthra 2021; Nimawat and Gidwani 2021; Pozzi, Rossi, and Secchi 2021
	11	Lack of lean production practices and continuous improvement approaches	Agostini and Filippini 2019; Pozzi, Rossi, and Secchi 2021
	12	Lack of stakeholders' involvement and engagement	Kumar, Vrat, and Shankar 2021; Chauhan, Singh, and Luthra 2021
	13	Vagueness in understanding Industry 4.0 and its strategic importance	Kumar, Vrat, and Shankar 2021; Stentoft et al. 2021; Majumdar, Garg, and Jain 2021; Cugno, Castagnoli, and Büchi 2021; Nimawat and Gidwani 2021
	14	Lack of collaboration between academic institutions and industry for innovation	Stentoft et al. 2021; Kumar, Vrat, and Shankar 2021; Cugno, Castagnoli, and Büchi 2021
	15	Too much focus on operational aspects and poor R&D on Industry 4.0 adoption	Stentoft et al. 2021; Majumdar, Garg, and Jain 2021; Nimawat and Gidwani 2021
Technological barriers	16	Lack of basic physical and digital IT infrastructure for data driven services and poor provision of broadband infrastructure and connectivity	Raj et al. 2020; Agostini and Filippini 2019; Kumar, Vrat, and Shankar 2021; Majumdar, Garg, and Jain 2021; Chauhan, Singh, and Luthra 2021; Cugno, Castagnoli, and Büchi (2021); Nimawat and Gidwani 2021; Pasi, Mahajan, and Rane (2020)
	17	Integration issues like compatibility, scalability and inter-operability between different machines, equipment, technologies and network systems	Kumar, Vrat, and Shankar 2021; Majumdar, Garg, and Jain 2021; Cugno, Castagnoli, and Büchi 2021; Nimawat and Gidwani 2021; Pasi, Mahajan, and Rane (2020)
	18	Low maturity level of the desired technology	Raj et al. 2020
	19	Resistance to share data due to lack of information security and privacy protection	Raj et al. 2020; Kumar, Vrat, and Shankar 2021; Stentoft et al. 2021; Majumdar, Garg, and Jain 2021; Chauhan, Singh, and Luthra 2021; Nimawat and Gidwani 2021; Pasi, Mahajan, and Rane (2020)
	20	Challenges in ensuring data quality	Raj et al. 2020; Chauhan, Singh, and Luthra 2021; Pasi, Mahajan, and Rane (2020)
Legal barriers	21	Lack of legal regulations to manage cybercrime and data theft	Kumar, Vrat, and Shankar 2021; Majumdar, Garg, and Jain 2021; Chauhan, Singh, and Luthra 2021; Cugno, Castagnoli, and Büchi (2021); Nimawat and Gidwani 2021; Pasi, Mahajan, and Rane (2020)
	22	Lack of standards and government regulations embracing Industry 4.0 regarding labour and employment and data ownership and copyright	Raj et al. 2020; Kumar, Vrat, and Shankar 2021; Stentoft et al. 2021; Majumdar, Garg, and Jain 2021; Chauhan, Singh, and Luthra 2021; Cugno, Castagnoli, and Büchi (2021); Nimawat and Gidwani 2021

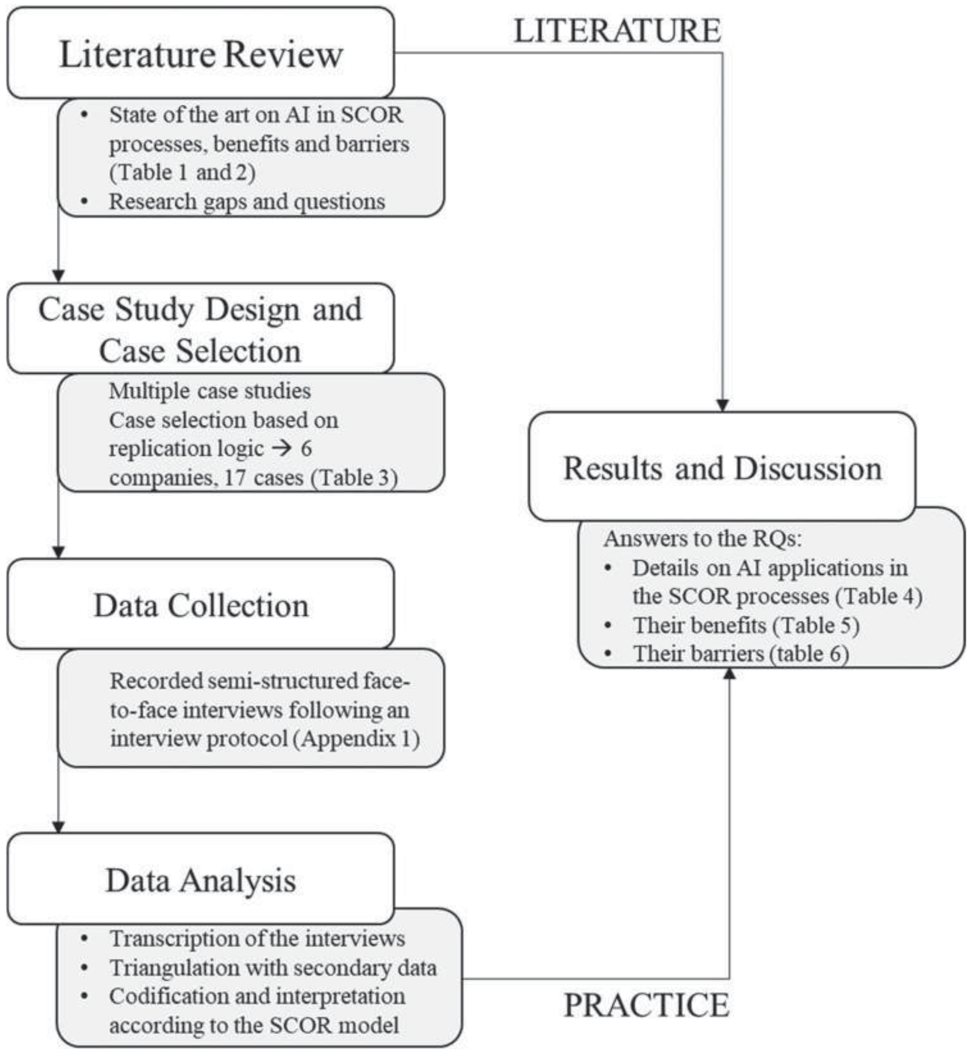

Figure 1. Summary of the research steps.

literature review with direct empirical observations through a case study methodology (see Figure 1). This qualitative research methodology, known to be 'oriented towards exploration, discovery and inductive logic' (Patton 2002), proves to be ideal for developing or broadening theories and providing empirical insights when the knowledge on a topic is scarce or few studies have been published on it (Jabbour et al. 2015). For AI, a topic that is certainly widely discussed but with still limited applications and only scarce empirical research in OSCM (Dubey et al. 2020; Helo and Hao 2021; Pournader et al. 2021), this methodology seems to adapt perfectly.

Case studies provide practical results that will not only help understand the topic, but also provide elements to guide its practical application (Eisenhardt 1989; Lisa M. Ellram 1996; R K Yin 2009). Moreover, case studies can provide detailed information that can go unnoticed in aggregate and top-down quantitative analyses (Carrillo-Hermosilla, del Río, and Könnölä 2010; Jabbour et al. 2015). A further value of case studies lies in the possibility of checking the validity of responses due to the nature of personal communication and interviewees, who are most certainly experts on the subject (Blome and Schoenherr 2011).

According to recent studies on case study research (Voss, Johnson, and Godsell 2016; Robert K Yin 2018), this study rigorously applies the following methodological steps: (i) case study design; (ii) case selection; (iii) data collection and analysis. To ensure the reliability of the research these steps are presented in detail in the following subsections.

3.1. Case study design

The methodology applied in this study involves multiple case studies. This methodology allows the authors to increase the external validity of the results owing to the possibility of collecting data from multiple cases

(Robert K Yin 2018). To limit variation and control for the research domain (Voss, Johnson, and Godsell 2016), this study addressed a population of companies operating in Italy. According to a recent report provided by the Italian Government (2022–2024), AI has vast potential, which is still not fully exploited. This report shows that there are a considerable number of players in the Italian market offering AI products, which are general in nature or for specific applications, and 53% of medium-large Italian companies declare that they have started at least one AI project, mostly belonging to the manufacturing sector. Therefore, companies operating in this country and successfully applying AI to support OSCM are particularly interesting to study, as they tackle barriers when implementing AI, but at the same time, can overcome them while many other companies are struggling. Thus, this study aims to analyse the AI solutions that companies operating in Italy are applying to support OSCM and understand the insights that can be gained on the benefits and barriers of AI in this field. It is possible to find more than one AI application within the same company; thus, the focus of this study and the unit of analysis is the AI application.

3.2. Case selection

The complete list of companies operating in the Italian manufacturing and service industries was extracted from the database 'AIDA' (https://aida.bvdinfo.com/), and only big companies (according to EU recommendation 2003/361) were selected because, from preliminary analyses, investments in AI require economic resources and skills that are more readily available in these types of companies. The unit of analysis of the study was the IA project because a company can apply several different solutions to overcome specific challenges. Within this predetermined list, the selection of cases accurately followed theoretical rationales, based on the logic of replication (Miles and Huberman 1994).

A total of six Italian companies were selected. These were considered an adequate number according to the logic of applied replication. In fact, the companies provided 17 cases and an appreciable amount of literal and theoretical replications that will be presented in the following sections, such as different and contrasting challenges to be faced, focus on different processes of the SCOR model, as well as several different AI tools and techniques adopted. These sample characteristics reinforce and support the findings of the study (Robert K Yin 2018).

A theoretical sampling based on replication logic (Eisenhardt 1989; Miles and Huberman 1994) was used for the selection of the cases: following the literal replication, AI applications were selected based on the expectation that they tackle similar barriers and have similar benefits, since they are all applied by companies operating in Italy, within the same economic and cultural context; following the theoretical replication, AI applications were selected based on the expectation that they face different contextual variables while being implemented, since they are all applied by companies that are heterogeneous in terms of sector, number of employees, and turnover. The information for selection was found on the companies' websites, universities, and consultancy reports. Moreover, the authors had experience with these companies because of their previous research projects. In total, six companies and 17 AI applications were selected. Table 3 provides an overview of the case study.

3.3. Data collection and analysis

Data collection was carried out through semi-structured face-to-face interviews to maintain a logical order while ensuring spontaneous deviation and open comments. The semi-structured interview, despite being based on subject directions found prior to the interview, allows the researcher to go in-depth for a discovery (Magaldi and Berler 2020). It offers both flexibility and the possibility to go further into topics while maintaining the focus of the study (Ruslin et al. 2022).

In this research, the participants were experts in AI (e.g. maintenance specialists, data science directors, and head of production process engineering) directly involved in or responsible for AI projects in their company and fully informed of the ongoing situation and problems. Each interview lasted approximately 120–180 minutes. In each company, there were at least two interviewees (see Table 3) to improve the validity (R K Yin 2009) and reliability of the collected data (Voss, Tsikriktsis, and Frohlich 2002). All interviews were recorded and transcribed verbatim.

The purpose of this study and the literature review linking AI and the OSCM processes formalised in the SCOR model reported in section 2 led the authors to define an interview protocol consisting of questions regarding: (i) general information about the company and the interviewee, (ii) details on benefits achieved when using AI to support OSCM, and (iii) details on barriers tackled when implementing AI to support OSCM. The interview protocol is reported in Appendix 1.

Furthermore, archival data, including annual reports, websites, and documents on AI projects, were used to triangulate empirical evidence and ensure multiple sources of evidence (Hays 2004; Stuart et al. 2002).

Table 3. Case study overview.

Company ID	Turnover 2021 [million €]	Number of employees 2021	Number of interviewee/s	Respondents' corporate role	Sector	Case study: AI application
A	2,198	4,654	2	Production Development Specialist Maintenance Specialist	Electronic components, automation and robotics	A1 = Visual Inspection for in process quality control A2 = Visual Inspection for product quality control A3 = Intelligent Cobot A4 = Predictive Maintenance
B	768	2,100	2	Data science Director	Manufacturer of pipes and related services for the world's energy industry	B1 = Prediction of industrial cost B2 = Anomaly detection system B3 = Virtual sensing system for scrap recovery
C	200	800	2	Maintenance Engineer Responsible for Engineering of Production Processes	Light firearms for hunting, sporting and personal defence	C1 = Classification of downtimes C2 = Predictive Maintenance C3 = Visual Inspection for product quality control
D	1,647	10,772	4	Program Manager	Manufacturer of electrical and semiconductor components	D1 = Anomaly detection system D2 = Intelligent batch dispatching system D3 = Virtual inspection for in process quality control D4 = Correlation analysis on electrical test results
E	71	536	2	HR Manager Supply Chain Manager	Textile	E1 = Optimisation of raw material replenishment
F	4,171	1,130	2	Operations Process Manager	Oil and Gas	F1 = Analysis and planning of the 'rebound' F2 = Intelligent interactive voice responder

3.4. Validity and reliability

This study aims to improve the validity and reliability of the analysis by adopting several strategies suggested by Eisenhardt (1989) and Yin (2009).

To ensure *construct validity*, we triangulated empirical evidence from multiple sources, as described in section 3.3. All interviews were recorded. For each case, a database was created containing verbatim transcripts of the interviews, archive data and field notes.

To ensure *reliability*, a protocol was followed during the fieldwork (see Appendix 1). Two authors manually conducted the coding and analysis of the interview and secondary data for each case; the few divergences in the initial codification were extensively discussed until an agreed final decision was reached, as suggested by Duriau, Reger, and Pfarrer (2007).

Internal validity was ensured by iteratively comparing the results of the analysis with the literature and the proposed model until theoretical saturation was reached.

To enhance the external validity, and thus the generalisability of the results, we adopted a theoretical sampling method based on the logic of replication (Eisenhardt 1989; Miles and Huberman 1994), detailed in section 3.1, and highlighted the similarities and differences in the cases analysed.

4. Results

4.1. AI applications support supply chain and operations management processes

Table 4 presents a summary of the AI applications identified by the companies analysed. The applications found within the cases are related to the plan, make, and deliver processes. Details are presented in the following sections.

4.1.1. Plan processes

Concerning demand planning and forecasting, Company F used to face a particularly critical situation due to a concentration of calls during customer billing periods. In those periods, there was an excessive lengthening of the waiting time before being able to talk to an operator, which generated a lot of complaints from customers. Therefore, they launched a project (F1) focused on the

Table 4. Results on AI applications in OSCM.

SCOR Processes	AI application in OSCM	Details on AI applications	Company [X] and AI solution [#]
Plan	Demand planning and forecasting	Analysis of historical demand data to forecast future customer demand to optimise the planning of the resources, plan marketing actions and balance workloads.	F1
	Inventory management	Analysis of raw material price trends, social media trends, and company's offer, to optimise raw material replenishment and achieve a good inventory management.	E1
Make	Scheduling	Analysis of conditions in the production department and resources' availability to rout batches in real-time to the various machines.	D2
	Manufacturing	Analysis of operators' gesture through visual control combined with cobot capabilities, to perform repetitive tasks, inspection, and quality control activities.	A3
		Analysis of variables related to systems behaviour to keep the production process constantly under control, set process limits and solve production problems detected in real time.	B2, D1
		Analysis of chemical elements within the scraps to optimise the recycling of scrap products, minimising the scraps purchasing cost and finding the best mix of scraps that complies the quality needed for the production system.	B3
	Quality	Analysis of process images or videos for in process quality control, to ensure process quality and automation, substitute the repetitive and alienating human control, and support root-cause analysis and decision-making.	A1, D3
		Analysis of product images or videos for product quality control, to measure the output of production, compare it to the production target and previous production.	A2, C3
		Analysis of product functioning to analyse the correlation between the physical measurements and the functioning of devices that fail tests and recognise configurations that can lead to test failures.	D4
	Maintenance	Analysis of machine functioning through sensors' data to identify the degree of 'health' and the degradation index of each individual machine (or its components), estimate the remaining useful life of the machines (or its components) and predict failures.	A4, C2
		Analysis of machine downtimes collected manually and through sensors to classify potential causes and support maintenance activities.	C1
Deliver	Process inquiry and quote	Analysis of historical data to identify relationships between industrial costs and product characteristics to predict future industrial costs of new build-to-order products and generate reliable quotations.	B1
		Analysis of speeches to improve automatic customer care and quickly and intuitively understand how to approach customer needs and problems.	F2

analysis and planning of the rebound, which is the peak of calls that the call centre receives from customers following the issuing of electricity and gas bills. The project leverages an ML algorithm that examines the 'rebound' history to forecast future customer calls, optimise the planning of the resources needed by the call centre to cover the possible demand curve, and guarantee a high customer service level. Additionally, this application has been used to plan marketing actions and scheduling when it is more effective in sending emails or messages about latest offers to avoid proposing commercial deals that could generate an overload of lines and operators.

Concerning inventory management, Company E, like many other companies in the fashion industry, faces a very specific problem. Fabric replenishment orders have very long lead times, and a lack of availability immediately turns into potential order losses. Conversely, an excess of stock has a big impact on working capital and high obsolescence costs. They developed a project (E1) for the optimisation of raw material replenishment and consequent good management of raw material inventories. This is an ML algorithm that suggests how to place raw material orders based on the analysis of data on events that can generate a purchase order: (i) historical prices of raw materials (e.g. the trend of silk price); (ii) information taken from different social media (e.g. trends related to colours or shapes); and (iii) customer samples (e.g. group of silk product samples offered to the buyers for presenting newly developed styles). This application has been used to balance stock-holding costs and customer service levels in a sector affected by high demand variability.

4.1.2. Make processes

As far as the scheduling process is concerned, for Company D the optimal planning of the batch launch becomes a key issue to guarantee adequate results in terms of efficiency and effectiveness. In the past, various solutions based on classical mathematical modelling tools have been developed and tested; however, these applications have shown major limitations as queues were forming in the departments, slowing down the production flow. The company developed a system for intelligent batch dispatching (D2) based on the reinforcement learning algorithm. This allows batches to be routed in real time to various machines based on the conditions in the production department and their availability. After several simulation trials, the system identifies different scenarios, including pessimistic scenarios, for example, a machine being down for a long time. This process is continuous, and the system defines and learns how to react to different situations.

Regarding manufacturing concerns, Company A had a critical issue with quality control activities in production. Since these controls were carried out in a robot work area, production had to be stopped. Furthermore, controls were visual and depending on who was doing the control, different outcomes could be obtained. They implemented a project (A3) concerning Intelligent Cobot, that is, a collaborative robot combined with AI, which can recognise operators' gestures through visual control. The cobot is used for repetitive tasks with low loads as well as for inspection and quality control activities. Company B developed two different projects (B2 and B3) in the manufacturing environment. When the furnace is restarted after a routine maintenance operation, the process leading to the ideal operating temperature is particularly critical and could have lethal effects on people working at the site. Therefore, they designed an anomaly detection system (B2) based on a neural network that is trained using data collected by the system's temperature sensors. This allows the estimation of the ideal operating temperature of the melting furnace and compares it with its actual value, thus maintaining the entire process under control. When a significant deviation is recorded between the data collected by the sensors and the ideal temperature predicted by the AI system, an early warning alarm is triggered, alerting operators to stop production, as there may be problems with product features or, in extreme cases, a risk of explosion. The second AI application (B3) was developed because they are not able to accurately determine the composition of the scrap used. The presence of low-quality scrap is indispensable for lowering the average cost of production; on the other hand, such scrap contains a high amount of polluting materials. The application is a virtual sensing system based on ML and estimates the content of chemical elements within the scraps. Based on these input data, the best combination of scraps of different quality (e.g. high-quality scrap, with very few pollutants, is represented by railways, while extremely low-quality scrap is represented by tuna cans, peeled tomatoes cans, etc., because they contain a lot of tin). The AI application is used to optimise the recycling of scrap products, minimising the scrap purchasing cost and finding the best 'recipe' that complies with the quality needed for the production system. In addition, Company B developed a project related to an anomaly detection system (B1) that analysed the data detected and collected by the machine sensors for temperature, pressure, gas flow, and electrical current used to check if the process is operating correctly. By analysing the standard curves of these parameters, it is possible to set limits that, if violated, categorise the process as a 'critical process'. These limits are extraordinarily complex to set, because various devices may have different responses. The introduction of an anomaly detection system based on ML has made it possible to analyse typical curves, learn from them, compare the parameters detected, and provide real-time engineering with an answer to the process.

Company A introduced two visual inspection methods to improve the quality of the production process. The first visual inspection tool (A1) operates on a robotic island that manages the assembly and screwing of a component. Before the component is closed and screwed on, it must be greased by the robot, which autonomously takes the piece and places it on top of the greasing tools. In this case, the AI application analyses images taken from the production process and assesses the amount of grease, and if it is placed correctly and in the correct positions. This allows the robot to work autonomously without human intervention, preventing an operator from personally checking each piece and substituting repetitive and alienating human control. The second visual inspection tool (A2) was applied to the switches' quality gate to measure the switches' insertion distance and torque. To assist this application, the company used a series of photographs, depicting the insertion distance; the photographs were analysed and used as input data using an ML tool that compares them to previous images and the production target, and defines the result of the quality test. In addition, Company C launched a visual quality control project (C3) because they needed to carry out an objective quality control to determine an adequate value for the weapon. An overestimated valuation can lead to damage the brand reputation, while an underestimated valuation can lead to a substantial loss of turnover. They installed a machine equipped with cameras within the over-and-under rifle line. This solution is based on deep learning algorithms; it can scan and recognise the quality of the wooden stocks of rifles by comparing them with models from a historical archive. Company D has developed two quality control projects. The first AI project (D3) applied image recognition to optical scans for quality control and defect testing during the production process of the wafer, a thin slice of semiconductor material, with defect positions. Subsequent analysis conducted by process engineering is required to understand how to treat the wafers, as not all defects necessarily lead to product rejection. An algorithm associated with image recognition supports root-cause analysis and aids in decision making. The second quality control project (D4) involved electrical testing, which was the ultimate step in the production process. The system is based on supervised and unsupervised ML algorithms to analyse the correlation between the results of electrical tests and physical measurements of devices that fail these tests. This would make it possible to recognise configurations that can lead to test failures before they reach the final stage and avoid work on failing devices.

An area of particular interest in AI applications is maintenance, mainly predictive maintenance, which is applied to automated processes. Company A developed a predictive model (A4) capable of estimating the remaining useful life of the machines (or their components) and predicting failures to achieve benefits in terms of costs and time. One of the components analysed was the electric motor, which provided a large amount of data, including temperature, torque absorbed, current, vibration, number of cycles, and maximum speed. Company C realised two algorithms based on ML techniques that were applied to several machines in the plant. The first algorithm (C1) determines the causes of downtime and classifies them by type. Data from the MES and ERP were used as inputs, as well as data provided by the maintenance managers, including the output of another algorithm indicating whether the machines were operational or stopped at a given time and how long they had been in one of the two states. This algorithm achieved reliability and accuracy of approximately 98%. The second application is a predictive maintenance tool (C2), which has been adopted for more than 60% of the company's machinery. This solution is based on a system called 'fingerprint' that allows the creation of a digital fingerprint capable of indicating the degree of 'health' and the degradation index of each individual machine, as well as the performance related to it. This makes it possible to intervene in the entire equipment, or only on a part of it, if it does not achieve the expected performance.

4.1.3. Deliver processes

As far as the delivery process is concerned, the companies analysed focused on their AI applications to support process enquiry and quote. Company B implemented an algorithm (B1) that predicted the cost of build-to-order products. In this case, the company does not know the cost of producing a product that it has never done before, and it is difficult to collect data to make these estimates. Furthermore, analysts starting with the same customer request can generate different quotations. Finally, analysts cannot estimate the consistency of a proposal. ML algorithms are objective and repeatable and can estimate uncertainty. To implement the solution, the firm collected a very large database of the actual costs of items already produced and trained the model to identify the relationships behind the data.

Additionally, to improve customer care, company F has developed an intelligent interactive voice responder (F2). In the past, the company used a traditional answering system, and the customer was forced to make three to four compulsory steps by typing the keys on the telephone several times before being able to speak to the operator. The new tool capable of identifying with an accuracy of 85% the customer on call by matching the phone number with the one recorded in the company database and using a series of disambiguation questions such as customer number, first and last name, and address. The special feature of this application allows the customer to provide his/her personal data by voice, like a normal conversation with an operator, instead of dialling a series of numbers and information, as done in the past. The AI voice responder understands the caller's basic needs and decides whether to forward the call immediately to the call centre or try to resolve the problem on its own and, only if this is not possible, to continue the call with an operator.

4.2. Benefits achieved by companies when using AI to support supply chain and operations management

The companies analysed highlighted the achievement of several benefits thanks to the use of AI to support OSCM.

Company A declared that the A1 project made it possible to improve the safety and reliability of processes and reduce lead times owing to the automation of human controls, whereas A2 established standard conditions to impartially verify whether a product corresponds to the reference model, generating a saving of 1.5 minutes per unit during quality control and increasing quality control. Applying AI to cobot (A3), instead, opened the possibility of interacting with the robot via gestures, allowing the 'gaming' effect. Through this new functionality, the company has achieved an increase in overall equipment effectiveness (OEE) and improved safety for operators working alongside the robot. Finally, the predictive maintenance project (A4) made it possible to reduce the lead time and maintenance costs, as well as improve the OEE.

Company B highlighted that project B1 allowed the firm to increase the reliability of the cost estimation, which reduced the response time of the quoting system from days to one-two seconds. In addition, human errors were significantly reduced, and the reliability of the quotation increased, with a consequent positive effect on the service level. The second project (B2) increases safety thanks to real-time monitoring of machines and simultaneously increases process reliability and OEE owing to the instant and quick intervention in the problems. Finally, the third project (B3) optimises the mix of scraps and reduces the purchasing costs of materials while ensuring high environmental sustainability by recycling scrap.

Table 5. Results on benefits of AI applications in OSCM.

		Plan		Make													Deliver		
		Demand planning and forecasting	Inventory Management	Scheduling	Manufacturing				Quality				Maintenance				Process Inquiry and quote		
Performance Category	Performance metrics	F1	E1	D2	A3	B2	D1	B3	A1	D3	A2	C3	D4	A4	C2	C1	B1	F2	Total
Cost	Reduction of costs	X	X					X		X			X	X	X			X	15
	OEE improvement			X	X	X								X	X	X			
	Stock rotation improvement		X																
Speed	Reduction of lead times								X		X		X	X	X	X	X		9
	Process reliability improvement					X			X										
Dependability	Service level improvement	X	X														X	X	4
Quality	Increased product quality						X				X	X							3
Safety	Safety improvement				X	X			X										3
Sustainability	Environmental sustainability improvement							X											1
	Total	5		1	8				9				8				4		

For Company C, the application of ML to maintenance (C1 and C2) made it possible to organise production with a view to necessary or planned maintenance work and reduced the average time to repair a fault by approximately 30 minutes. They also generated a 4% gain in machine availability, thereby improving the OEE. Moreover, quality control through the AI application C3 increased product quality by reducing the reliability of controls and the 'false positive' results in the quality check.

Company D stated that project D1 enhanced the root-cause analysis and supported the improvement of the finished product quality, an essential performance in the semiconductor industry. The system for the intelligent batch (D2) increased the number of batches leaving the production line, creating a more continuous and constant flow. The benefit of the image recognition system (D3) was cost reduction due to the reduction in scrap rate, as not all defective wafers necessarily have to be eliminated, and some of them can be recovered. The fourth project (D4) allows a considerable reduction in costs, as well as more time and margin of action to implement possible safeguards and countermeasures.

Company E underlined that project E1 made more accurate order forecasting possible and allowed for the optimal investment of available capital based on price trends and transportation costs, being able to prioritise certain materials and fabrics that are difficult to find and for which stock availability directly affects customer delivery times. This favours operational benefits with low purchasing, high rotation turnover for raw materials, and an increased service level. From a quantitative perspective, the application of the ML algorithm resulted in a 30% reduction in stock.

Finally, Company F presented the F1 project as an application that allowed the internal resources of the call centre to be saturated, keeping costs low, and improved the management of peaks, reducing unmet demand, and increasing service level. Owing to the use of the AI algorithm, it is possible to reduce the abandonment rate, minimise disruption, and reduce operating costs. The advantage of the intelligent interactive voice responder (F2) is that it enriches communication and humanises an interaction with the customer that was previously cold and aseptic. This application improves the customer experience by reducing waiting time when switching to an operator and reducing operating costs, as a call handled by the call centre costs much more than a voice responder call.

Table 5 presents a summary of the main results obtained from the cases. Since the benefits have been measured by companies through performance metrics that were improved thanks to AI projects, the results were categorised, as suggested by Slack, Chambers, and Johnston (2010), into the operational performance dimensions. In particular, cost resulted as the dimension that took the most advantage from AI projects, followed by speed, dependability, and quality. Additionally, a small

Table 6. Results on barriers to AI implementation in OSCM.

Category	ID	Barriers	Companies
Financial barriers	1	High investment needed to implement AI initiatives, insufficient financial resources within the company and scarcity of external financing	A, E, F
	2	Lack of clarity regarding the economic benefit and low experience in budgeting, cost analysis, resource allocation, etc.	A, C, F
Organisational barriers	4	Enhanced skills required for employees, shortage of workforce with adequate skillset in the labour market and lack of internal training	A, B, C, D, F
	5	Lack of internal digital culture and training to embrace technological advancements	A
	6	Lack of employees' readiness and high resistance to change	A, F
	7	Lack of knowledge management systems and low integration and collaboration among organisation departments and supply chain partners	C, D
Strategical barriers	8	Difficult process changes and ineffective change management	D
Technological barriers	17	Integration issues like compatibility, scalability and interoperability between different machines, equipment, technologies, and network systems	E
	20	Challenges in ensuring data quality	A, B, D, E, F

number of cases underlined safety and sustainability as further benefits.

4.3. Barriers tackled by companies when implementing AI to support supply chain and operations management

The results of this study underlined nine main barriers tackled by companies when implementing AI projects, belonging to the financial, organisational, strategic, and technological categories. Table 6 summarises the obtained results, which are detailed below.

The main barriers faced by Company A lie in the high complexity of data collection caused by the variability of the products offered, both in terms of the size and number of components. A representative example is the retrieval of photos of all possible switch configurations, which requires a huge amount of time and internal resources to provide all the information, as well as the huge investment needed to conduct the data capture process without a clear return on investment (ROI). Furthermore, with the implementation of the AI cobot (A3), Company A experienced some preliminary mistrust from operators towards a new technology that had never been used before.

Company B has faced difficulties in creating a consistent database. It is based on the consistency of the database that the effectiveness of an AI system derives: the higher the quality of the data collected, the more the developed model will be able to return truly useful output in terms of predictions or suggestions. Another point of focus is the reliability of the system. Often, the AI system is erroneously considered to always be reliable, and as a result, the suggested solution is accepted uncritically. Instead, it must be considered that, even though the AI model has undergone an adequate learning process, there is still a probability that it may provide answers that are not necessarily correct. Another critical aspect that was emphasised concerns the availability of specific knowledge and skills, both concerning the internal production processes being addressed and development of AI models.

Company C highlighted the lack of cross-competencies to build an interfunctional team dealing with such projects. To overcome this problem, all AI projects have been implemented by combining internal and external expertise from consulting firms and universities. Interviewees highlighted a second barrier in assessing the possible benefits derived from the adoption of AI tools compared to the implementation costs incurred without a clear ROI. Another barrier encountered by the company is the lack of replicability due to the bottom-up AI project approach.

Company D focused on three main issues in the development of AI projects. The first is related to data in terms of the complexity of the data collection, preparation, and storage processes. The company had to develop an effective infrastructure to support the collection, preparation, and cleaning of data from various sources. The data management process requires a great deal of standardisation because the production equipment is provided by different suppliers and follows different standards, which increases the data management. The other two barriers concern organisational hurdles. The first is the establishment of a change-oriented corporate mindset and culture, as not all internal resources have the skills necessary to manage these new technologies. The second problem is the initial bottom-up approach used by the firm to implement AI projects as it reduces the standardization/replicability of the project on other sites.

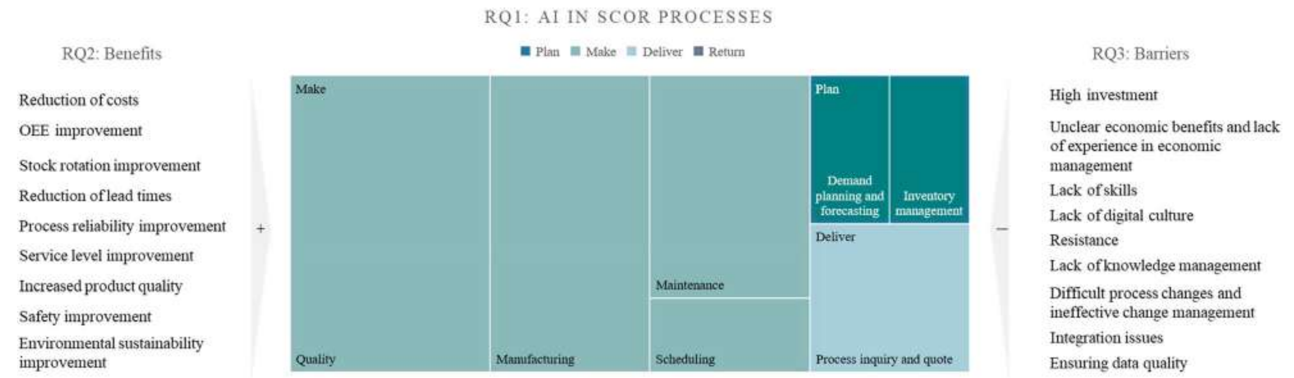

Figure 2. Summary of the main results and discussions.

The main barrier encountered by Company E is the limited availability of economic resources for investment. Another major barrier is the sector's particularly advanced technologies, a consequence of the lack of adequate capital to invest in supporting technological innovation. For example, the company finds it difficult to move into the area of predictive maintenance because its suppliers of production equipment have not, to date, offered this type of service included in machinery, which would require sensors and data analytics systems to identify deviations in plant behaviour and predict problems before they occur.

Company F has identified three main issues in the development of AI projects. The first is the creation of a data-driven company culture, which is important for the implementation of a suitable IT infrastructure for collecting, storing, preparing, and analysing data. Another critical issue is the ability to decide which AI project to develop because the investments are extremely high and take a long time to implement, and subsequently generate an uncertain value and ROI. The last critical issue is finding people who have the skills and abilities to implement such technologies. It is often necessary to turn to external consultancies that can support, at least in the initial stages, the development of the project and provide the appropriate skills that are not available within the company.

5. Discussion

This study empirically investigates 17 AI projects implemented by six companies. For each SCOR process, the AI projects adopted to support the supply chain and operations processes were defined, thus providing an answer to RQ1. The benefits achieved for each AI project were then reported, providing an answer to RQ2. Finally, the main barriers encountered by companies in implementing AI were classified to provide answers to RQ3. A summary is depicted in Figure 2.

5.1. *Answering RQ1: how do AI applications support supply chain and operations management processes?*

Using the SCOR classification, most of the projects (13 out of 17) involved make processes, with a focus on manufacturing, quality, and maintenance applications. Two projects involved the plan process, with a particular focus on demand planning and forecasting and inventory management applications, and two involved the deliver process, with a particular focus on process enquiry and quote applications. The focus on make processes can be commented on by observing the concentration of expected benefits, detailed in the next paragraph, on the dimensions of time and cost reduction, and improvement of production efficiency. In this phase of the life cycle of AI technologies, the need to justify investments made by seeking tangible benefits through their implementation may be predominant. From this perspective, any improvement in production processes can generate faster returns on the resources invested.

Almost all the applications developed for quality control are based on image-processing solutions. Despite the critical issues highlighted by some authors regarding the performance of these systems in particular environmental conditions (Dai et al. 2021), the cases analysed show how companies have identified in the image analysis solutions, particularly effective tools for searching and classifying defects, with the aim of preventing nonconformities from ending up in the market, and improving the production process due to a more accurate analysis of the defects themselves (for example, any recurrence of specific types of defects, of parts of the product where the defects are concentrated, etc.).

Applications related to manufacturing are more varied, but one that has come up in more cases is the analysis of variables related to the behaviour of systems to constantly monitor the process and solve production problems detected in real time. Applications for predictive maintenance are all related and concern the estimation of the health status and lifetime of a machine, prediction of failures, and classification of their causes. All these applications are enabled by the context of smart manufacturing, where the vertical integration of the company allows heterogeneous data from the shop floor to be collected in real time through sensors and merged and handled in MES and ERP systems.

5.2. Answering RQ2: what are the benefits achieved by companies when using AI to support supply chain and operations management?

As already mentioned in the previous paragraph, AI projects that have been implemented by companies have had an impact on reducing costs and improving the efficiency of production processes, confirming what has emerged in recently published studies (see Table 1). Considering that multiple responses were possible regarding the performance achieved by the projects, cost reduction, lead time reduction, and OEE were the ones mostly covered by the cases analysed, achieving concrete benefits on these three dimensions. Most of the answers on the improvements highlighted a direct impact in terms of lower production costs or efficiency gains. Another significant set of responses was related to the improvement of service level and quality, to increase external performance perceived by the customer and safety, to determine a positive impact on the working conditions of the operators, an objective not so obvious, and, above all, not always a priority in company policies. The residual part of the answers consists of improvements concerning process reliability, environmental sustainability, and the stock rotation index.

It may be interesting to highlight the processes in which the benefits achieved are mainly concentrated. There is a clear concentration in the make process, especially regarding quality applications, for which improvements have been obtained both in terms of product and process quality and efficiency. These results are consistent with the adoption of image processing solutions, in terms of reducing costs and increasing the efficiency of the quality control processes themselves. Maintenance and manufacturing applications also have several benefits. Maintenance benefits are concentrated on process efficiency and improvement by reducing lead times and costs and improving OEE. Manufacturing applications have various effects, with benefits focused on safety, environment, and process reliability.

5.3. Answering RQ3: what are the barriers tackled by companies when implementing AI to support supply chain and operations management?

From the analysis of the barriers that can hinder or slow down the process of implementing AI solutions within companies, three distinct sets emerge: barriers that concern the more technical aspects of the implementation processes, barriers related to the more strategic-organisational aspects, and barriers related to financial aspects.

Focusing on the more technical dimensions, the sample of companies investigated highlighted the complexity inherent in the process of collecting the data necessary to feed the algorithms underlying the implemented AI solutions. The necessary condition for maximising the learning process of ML and DL systems is the availability of large quantities of high-quality data. The more the data available, the more frequently they are updated, and the more differentiated forms they come in, the better the ability of the algorithm to learn and produce accurate outputs. Five companies substantially confirm what emerges from the analysis of the main contributions that have appeared in the literature, highlighting the issue of data quality as the main barrier to implementation due to a low ability to govern the data acquisition processes and the subsequent archiving and processing phases. They underlined the difficulty of building a sufficiently consistent and reliable database to feed the learning process of AI algorithms, and the criticality of the data acquisition process correlated with the constraints posed by the machines currently in use.

Concerning the strategic-organisational dimension, five companies involved in the research reported a lack of adequate technical skills to support the development and implementation of AI solutions as another significant problem. This aspect is a particularly critical issue because it is evident that today, we are facing a structural deficit of figures with a technical background that respond to the concrete needs of companies that intend to start AI projects. From the interviews, it emerges that the path of upskilling and reskilling of figures already present in the company appears to be impractical today, as the skills to be developed are very specific, and for the management of these projects, it is necessary to have already acquired a certain amount of experience because the problems to be faced are often poorly codified. To complete these reflections, it should also be noted that the AI phenomenon is relatively recent regarding business applications; therefore, several companies have not yet developed the models and tools required to identify and select the necessary AI skills. Additional evidence emerged from the cases is identified in the absence of an adequate culture of change that can support organisational structures and individuals in the adoption of technological solutions that can also have significant impacts on processes and areas of comfort that have been created over the years. However, there is also an issue of lack of readiness from operators, low integration and collaboration among organisational departments and supply chain partners, difficult process changes, and ineffective change management.

In terms of financial aspects, four companies highlighted the financial dimension as a significant barrier to AI adoption. They reported that both the amount of investment required to develop and implement the projects and the difficulty in determining the potential return on investment with a reasonable degree of reliability. These results also confirm the indications that emerged in several studies that reported a lack of financial resources to support the necessary investments and scepticism about achieving a sufficient return on investment from AI solutions as obstacles. This last aspect can represent an important break for those companies that require very precise analyses of the expected returns to authorise investments, and that embrace a very short-term culture for which actions with certain and immediate impacts are preferred, even if not particularly consistent under the economic profile.

A final consideration relates to the absence of evidence on two factors which often find specific findings in the literature (see Table 2). The companies investigated did not highlight any problems on front of the commitment and buy-in of the top management. Usually, in such large-scale projects, as well as in lean transformation projects or ERP system implementation projects, these elements are often cited as the causes of failure. Similarly, no specific evidence has emerged on the IT security front associated with the adoption of AI solutions. However, since the analysed companies represent successful cases in the implementation of AI projects, they have probably overcome these criticalities, thanks to a series of prerequisites already satisfied, that is, top management commitment and cyber security contracts with suppliers. Rather, they have highlighted only the most relevant barriers still representing real complex obstacles to be overcome, even for future projects.

6. Conclusion

The aim of this study is to investigate the applications of AI to OSCM through the experiences and insights of real industrial cases. The study aims to analyse how AI applications support OSCM in various specific processes and to investigate benefits achieved and barriers faced by companies in their implementation. To do so, this research conducts multiple case studies. It analyses empirical data concerning 17 applications of AI to the SCOR processes within six Italian companies.

6.1. Contribution to theory

From a theoretical perspective, this study increases the understanding of AI applications to support OSCM processes and specifically the SCOR processes. The results of the literature review show applications of AI in the five SCOR processes, identify benefits for companies in OSCM, and analyse the main barriers to implementation that companies may face during the implementation of Industry 4.0, which includes AI among its technologies. Very few studies have empirically tackled these issues before, although recent studies have emphasised the importance of exploring the topic and deepening and refining the literature (Nikseresht et al. 2022; Wilson, Paschen, and Pitt 2021). Previous studies have primarily focused on the development of new AI algorithms, testing them via simulations or single experimental cases, or proposing literature reviews on the topic without any empirical data.

The discussion of the findings of this study shows how the cases provide new observations, build on the literature, and introduce interesting new concepts that will advance the theory and practice of AI in OSCM. The potential applications and benefits identified in the literature have been enriched by the inclusion of real companies' perspectives. The analysed companies concentrated their AI applications to support the make processes, with a focus on manufacturing, quality, and maintenance applications. These applications made it possible for companies to achieve concrete benefits in three performance dimensions: cost reduction, lead time reduction, and OEE. In addition, this study analysed barriers that concern AI implementation, which has resulted in very little coverage by recent studies, and only some technical barriers related to the development of specific ML algorithms have been identified. The results of the case research, starting from barriers related to Industry 4.0 implementation, which includes AI among its technologies, show that the key barriers faced by the companies analysed are related to technical, strategic-organisational, and financial aspects.

6.2. Contribution to practice

From an empirical perspective, this study reports and analyses several projects of AI application to OSCM processes within real companies. At present, practitioners can find very few models or indications based on empirical data in the literature. This study fills this gap and provides practitioners with practical examples of AI applications to OSCM using a process-based perspective. This perspective can inspire and guide pilot projects on targeted processes, such as those that create bottlenecks or those that contribute most to value creation. In addition, the results of this study can also make managers and practitioners aware of the possible challenges and benefits that can be encountered during the implementation and the performance to be assessed to verify the effectiveness of the projects.

6.3. Limitations and future research

The main limitation of this study lies in the nature of the methodology adopted. Although multiple case studies are broadly acknowledged as a robust research method for theory building (Voss, Johnson, and Godsell 2016; Robert K Yin 2018), it is also true that it is a qualitative methodology based on a limited set of companies, which makes it possible to deeply analyse cases but difficult to generalise the results obtained. Moreover, in this study, the cases were all carried out in the same geographical context, i.e. Italy. The study adopted various strategies to support validity and reliability (see section 3.4), but caution must be exercised in generalising the results of this study to a larger population.

The results of this study could be validated by future research by replicating this study with a different sample or by conducting a quantitative study on a larger population.

Despite its limitations, the study provides interesting and novel results, presenting clear insights into the use of AI in various processes of the SCOR model. Future studies could further explore the use of AI in 'return' processes. They could also take inspiration from the recent developments of the Association for Supply Chain Management (ASCM), which extends the processes view given by the SCOR with one based on Digital Capabilities, summarised in the Digital Capabilities Model (DCM). According to the ASCM, in the DCM 'each digital capability is mapped to relevant elements in the SCOR Digital Standard'[1]ï£ij. This possible future research direction would integrate the two views to provide a comprehensive guide to the implementation of AI in OSCM. Studying the processes to understand the capabilities required is fundamental and this study provided the basis for this.

Note

1. https://www.ascm.org/corporate-transformation/dcm/

Acknowledgements

We would like to express our gratitude to the Italian Ministry of Universities and Research (MUR) for their funding support to the author Violetta Giada Cannas through the PON research contract on innovation, enabling technologies, and the broader theme of digitalization.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes on contributors

Violetta Giada Cannas, Ph.D. is an Assistant Professor at the School of Industrial Engineering of Carlo Cattaneo University (LIUC). She teaches Operations management, Quality management and Smart Factory at LIUC, and Operations Management at the School of Management of Politecnico di Milano. She is also part of the team that work in the i-FAB LIUC, a learning factory for the adoption of Industry 4.0 technologies in a lean-managed assembly system. Her research interests include supply chain and production management, lean management, and Industry 4.0, with a particular focus on companies operating in the engineer-to-order context.

Maria Pia Ciano, Ph.D. is Assistant Professor in Operations Management at the Business School of the University of Nottingham. She teaches modules on Logistics and Supply Chain Management, Technology and Organisation, and Plant Location and Design. She completed her PhD at LIUC Carlo Cattaneo University with a thesis titled 'Towards an industrial transformation: the link between Lean techniques and Industry 4.0 technologies'. Her main research topics and interests are: Lean Manufacturing and Supply Chain, Industry 4.0, Industry 5.0, and the research areas that can derive from or link these topics, such as Data Analytics and Circular Economy.

Raffaele Secchi is Full Professor of Operations and Supply Chain Management at LIUC – Università Cattaneo, Castellanza. He is also Dean of LIUC Business School. He is Visiting Professor at IESEG Business School. He has authored or co-authored several articles, book chapters, and four books on operations and supply chain management. His research appeared in International Journal of Operations and Production Management, International Journal of Production Economics, Industrial Marketing Management and Production Planning & Control.

Mattia Saltalamacchia is a teaching assistant at the School of Economics of Carlo Cattaneo University (LIUC). Currently he is a PhD student under the supervision of Prof. Raffaele Secchi at the same School. His main topics of interest and research are: Lean Management, Operations Management, Artificial Intelligence, Customer Journey, Industry 4.0, and performance improvement.

Data availability statement

The data that support the findings of this study are available from the corresponding author, Maria Pia Ciano (maria.ciano@nottingham.ac.uk), upon reasonable request.

References

Abbas Naqvi, Mohammad, and Saman Hassanzadeh Amin. 2021. "Supplier Selection and Order Allocation: A Literature

Review." *Journal of Data, Information and Management*, 125–139. https://doi.org/10.1007/s42488-021-00049-z.

Agostini, Lara, and Roberto Filippini. 2019. "Organizational and Managerial Challenges in the Path Toward Industry 4.0." *European Journal of Innovation Management* 22 (3): 406–421. https://doi.org/10.1108/EJIM-02-2018-0030.

Aktepe, Adnan, Emre Yanık, and Süleyman Ersöz. 2021. "Demand Forecasting Application with Regression and Artificial Intelligence Methods in a Construction Machinery Company." *Journal of Intelligent Manufacturing* 32 (6): 1587–1604. https://doi.org/10.1007/s10845-021-01737-8

APICS. 2017. *Supply Chain Operations Reference Model Version 12.0*. http://www.emeraldinsight.com/doi/10.110809576059710815716.

Bahadori, Mohammadkarim, Seyed Morteza Hosseini, Ehsan Teymourzadeh, Ramin Ravangard, Mehdi Raadabadi, and Khalil Alimohammadzadeh. 2020. "A Supplier Selection Model for Hospitals Using a Combination of Artificial Neural Network and Fuzzy VIKOR." *International Journal of Healthcare Management* 13 (4): 286–294. https://doi.org/10.1080/20479700.2017.1404730.

Bai, Chunguang, Patrick Dallasega, Guido Orzes, and Joseph Sarkis. 2020. "Industry 4.0 Technologies Assessment: A Sustainability Perspective." *International Journal of Production Economics* 229: 107776. https://doi.org/10.1016/j.ijpe.2020.107776

Bala, P. K. 2012. "Improving Inventory Performance with Clustering Based Demand Forecasts." *Journal of Modelling in Management* 7 (1): 23–37.

Baryannis, George, Sahar Validi, Samir Dani, and Grigoris Antoniou. 2019. "Supply Chain Risk Management and Artificial Intelligence: State of the Art and Future Research Directions." *International Journal of Production Research* 57 (7): 2179–2202. https://doi.org/10.1080/00207543.2018.1530476

Belhadi, Amine, Sachin Kamble, Samuel Fosso Wamba, and Maciel M. Queiroz. 2022. "Building Supply-Chain Resilience: An Artificial Intelligence-Based Technique and Decision-Making Framework." *International Journal of Production Research* 60 (14): 4487–4507. https://doi.org/10.1080/00207543.2021.1950935.

Benitez, Guilherme Brittes, Néstor Fabián Ayala, and Alejandro G Frank. 2020. "Industry 4.0 Innovation Ecosystems: An Evolutionary Perspective on Value Cocreation." *International Journal of Production Economics* 228: 107735. https://doi.org/10.1016/j.ijpe.2020.107735

Birkel, Hendrik, and Julian M Müller. 2021. "Potentials of Industry 4.0 for Supply Chain Management Within the Triple Bottom Line of Sustainability–A Systematic Literature Review." *Journal of Cleaner Production* 289: 125612. https://doi.org/10.1016/j.jclepro.2020.125612

Blome, Constantin, and Tobias Schoenherr. 2011. "Supply Chain Risk Management in Financial Crises—A Multiple Case-Study Approach." *International Journal of Production Economics* 134 (1): 43–57. https://doi.org/10.1016/j.ijpe.2011.01.002.

Cadden, Trevor, Denis Dennehy, Matti Mantymaki, and Raymond Treacy. 2022. "Understanding the Influential and Mediating Role of Cultural Enablers of AI Integration to Supply Chain." *International Journal of Production Research* 60 (14): 4592–4620. https://doi.org/10.1080/00207543.2021.1946614

Cantini, Alessandra, Mirco Peron, Filippo De Carlo, and Fabio Sgarbossa. 2022. "A Decision Support System for Configuring Spare Parts Supply Chains Considering Different Manufacturing Technologies." *International Journal of Production Research*, 1–21. https://doi.org/10.1080/00207543.2022.2041757

Carrillo-Hermosilla, Javier, Pablo del Río, and Totti Könnölä. 2010. "Diversity of Eco-Innovations: Reflections from Selected Case Studies." *Journal of Cleaner Production* 18 (10-11): 1073–1083. https://doi.org/10.1016/j.jclepro.2010.02.014.

Carvalho, Thyago P., Fabrízzio A.A.M.N. Soares, Roberto Vita, Roberto da P. Francisco, João P. Basto, and Symone G.S. Alcalá. 2019. "A Systematic Literature Review of Machine Learning Methods Applied to Predictive Maintenance." *Computers & Industrial Engineering* 137 (November): 106024. https://doi.org/10.1016/j.cie.2019.106024.

Chan, Felix T.S., Anuj Prakash, and Nishikant Mishra. 2013. "Priority-Based Scheduling in Flexible System Using AIS with FLC Approach." *International Journal of Production Research* 51 (16): 4880–4895. https://doi.org/10.1080/00207543.2013.774500.

Chauhan, Chetna, Amol Singh, and Sunil Luthra. 2021. "Barriers to Industry 4.0 Adoption and Its Performance Implications: An Empirical Investigation of Emerging Economy." *Journal of Cleaner Production* 285: 124809. https://doi.org/10.1016/j.jclepro.2020.124809

Chehbi-Gamoura, Samia, Ridha Derrouiche, David Damand, and Marc Barth. 2020. "Insights from Big Data Analytics in Supply Chain Management: An All-Inclusive Literature Review Using the SCOR Model." *Production Planning and Control* 31 (5): 355–382. https://doi.org/10.1080/09537287.2019.1639839.

Chen, Ming Kuen, Teng Wang Tai, and Tsu Yi Hung. 2012. "Component Selection System for Green Supply Chain." *Expert Systems with Applications* 39 (5): 5687–5701. https://doi.org/10.1016/j.eswa.2011.11.102.

Cugno, Monica, Rebecca Castagnoli, and Giacomo Büchi. 2021. "Openness to Industry 4.0 and Performance: The Impact of Barriers and Incentives." *Technological Forecasting and Social Change* 168: 120756. https://doi.org/10.1016/j.techfore.2021.120756

Dai, W., D. Li, D. Tang, Q. Jiang, D. Wang, H. Wang, and Y. Peng. 2021. "Deep Learning Assisted Vision Inspection of Resistance Spot Welds." *Journal of Manufacturing Processes* 62: 262–274. https://doi.org/10.1016/j.jmapro.2020.12.015.

Dhamija, Pavitra, and Surajit Bag. 2020. "Role of Artificial Intelligence in Operations Environment: A Review and Bibliometric Analysis." *TQM Journal* 32 (4): 869–896. https://doi.org/10.1108/TQM-10-2019-0243.

Dosdoğru, Ayşe Tuğba, Aslı Boru İpek, and Mustafa Göçken. 2021. "A Novel Hybrid Artificial Intelligence-Based Decision Support Framework to Predict Lead Time." *International Journal of Logistics Research and Applications* 24 (3): 261–279. https://doi.org/10.1080/13675567.2020.1749249.

Dubey, Rameshwar, Angappa Gunasekaran, Stephen J. Childe, David J. Bryde, Mihalis Giannakis, Cyril Foropon, David Roubaud, and Benjamin T. Hazen. 2020. "Big Data Analytics and Artificial Intelligence Pathway to Operational Performance Under the Effects of Entrepreneurial Orientation and Environmental Dynamism: A Study of Manufacturing

Organisations." *International Journal of Production Economics* 226 (December 2019): 107599. https://doi.org/10.1016/j.ijpe.2019.107599.

Duriau, Vincent J., Rhonda K. Reger, and Michael D. Pfarrer. 2007. "A Content Analysis of the Content Analysis Literature in Organization Studies: Research Themes, Data Sources, and Methodological Refinements." *Organizational Research Methods* 10 (1): 5–34. https://doi.org/10.1177/1094428106289252.

Dutta, Pankaj, Sahil Talaulikar, Vinay Xavier, and Shubham Kapoor. 2021. "Fostering Reverse Logistics in India by Prominent Barrier Identification and Strategy Implementation to Promote Circular Economy." *Journal of Cleaner Production* 294: 126241. https://doi.org/10.1016/j.jclepro.2021.126241

Eisenhardt, Kathleen M. 1989. "Building Theories from Case Study Research." *Academy of Management Review* 14 (4): 532–550. https://doi.org/10.2307/258557.

Ellefsen, Anna Paula Tanajura, Joanna Oleśków-Szłapka, Grzegorz Pawłowski, and Adrianna Toboła. 2019. "No Title." *Logforum* 15 (3): 363–376. https://doi.org/10.17270/J.LOG.2019.354.

Ellram, Lisa M. 1996. "The Use of the Case Study Method in Logistics Research." *Journal of Business Logistics* 17 (3): 93–138.

Encapera, Angelo, Abhijit Gosavi, and Susan L. Murray. 2021. "Total Productive Maintenance of Make-to-Stock Production-Inventory Systems via Artificial-Intelligence-Based ISMART." *International Journal of Systems Science: Operations & Logistics* 8 (2): 154–166. https://doi.org/10.1080/23302674.2019.1707906.

Fallahpour, Alireza, Yew Wong Kuan, Udoncy Olugu Ezutah, and Siti Nurmaya Musa. 2017. "A Predictive Integrated Genetic-Based Model for Supplier Evaluation and Selection." *International Journal of Fuzzy Systems* 19), https://doi.org/10.1007/s40815-017-0324-z.

Fashoto, Stephen Gbenga, Akinnuwesi Boluwaji, Owolabi Olumide, and Adelekan David. 2016. "Decision Support Model for Supplier Selection in Healthcare Service Delivery Using Analytical Hierarchy Process and Artificial Neural Network." *African Journal of Business Management* 10 (9): 209–232. https://doi.org/10.5897/AJBM2016.8030.

Fosso Wamba, Samuel, Maciel M. Queiroz, Cameron Guthrie, and Ashley Braganza. 2021. "Industry Experiences of Artificial Intelligence (AI): Benefits and Challenges in Operations and Supply Chain Management." *Production Planning and Control* 0 (0): 1–13. https://doi.org/10.1080/09537287.2021.1882695.

Frank, Alejandro Germán, Lucas Santos Dalenogare, and Néstor Fabián Ayala. 2019. "Industry 4.0 Technologies: Implementation Patterns in Manufacturing Companies." *International Journal of Production Economics* 210: 15–26. https://doi.org/10.1016/j.ijpe.2019.01.004

Gegovska, T., R. Köker, and T. Çakar. 2020. "Green Supplier Selection Using Fuzzy Multiple-Criteria Decision-Making Methods and Artificial Neural Networks." *Computational Intelligence and Neuroscience*. https://doi.org/10.1155/2020/8811834.

Guo, Xuesong, Zhiping Yuan, and Bojing Tian. 2009. "Supplier Selection Based on Hierarchical Potential Support Vector Machine." *Expert Systems with Applications* 36 (3): 6978–6985. https://doi.org/10.1016/j.eswa.2008.08.074.

Hamdan, Sadeque, and Anwar Jarndal. 2017. *A Two Stage Green Supplier Selection and Order Allocation Using AHP and Multi-Objective Genetic Algorithm Optimization*. https://doi.org/10.1109/ICMSAO.2017.7934843.

Hays, Patricia A. 2004. "Case Study Research." In *Foundations for Research: Methods of Inquiry in Education and the Social Sciences*, edited by Kathleen deMarrais, and Stephen D. Lapan, 217–234. Mahwah, New Jersey: Lawrence Erlbaum Associates, Inc.

Helo, Petri, and Yuqiuge Hao. 2021. "Artificial Intelligence in Operations Management and Supply Chain Management: An Exploratory Case Study." *Production Planning and Control* 0 (0): 1–18. https://doi.org/10.1080/09537287.2021.1882690.

Hill, Alessandro, and Jürgen W. Böse. 2016. "A Decision Support System for Improved Resource Planning and Truck Routing at Logistic Nodes." *Information Technology and Management* 18: 241–251. https://doi.org/10.1007/s10799-016-0267-3.

Islam, Samiul, Saman Hassanzadeh Amin, and Leslie J. Wardley. 2021. "Machine Learning and Optimization Models for Supplier Selection and Order Allocation Planning." *International Journal of Production Economics* 242 (December): 108315. https://doi.org/10.1016/j.ijpe.2021.108315.

Jabbour, Charbel José Chiappetta, Angelo Saturnino Neto, José Alcides Gobbo, Maisa de Souza Ribeiro, and Ana Beatriz Lopes de Sousa Jabbour. 2015. "'Eco-Innovations in More Sustainable Supply Chains for a Low-Carbon Economy: A Multiple Case Study of Human Critical Success Factors in Brazilian Leading Companies." *International Journal of Production Economics* 164 (June): 245–257. https://doi.org/10.1016/j.ijpe.2014.11.015.

Kamble, Sachin S, Angappa Gunasekaran, Abhijeet Ghadge, and Rakesh Raut. 2020. "A Performance Measurement System for Industry 4.0 Enabled Smart Manufacturing System in SMMEs-A Review and Empirical Investigation." *International Journal of Production Economics* 229: 107853. https://doi.org/10.1016/j.ijpe.2020.107853

Kantasa-ard, Anirut, Maroua Nouiri, Abdelghani Bekrar, Abdessamad Ait el cadi, and Yves Sallez. 2021. "Machine Learning for Demand Forecasting in the Physical Internet: A Case Study of Agricultural Products in Thailand." *International Journal of Production Research* 59 (24): 7491–7515. https://doi.org/10.1080/00207543.2020.1844332.

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

Khashei, Mehdi, and Fatemeh Chahkoutahi. 2021. "Electricity Demand Forecasting Using Fuzzy Hybrid Intelligence-Based Seasonal Models." *Journal of Modelling in Management* 17 (1): 154–178. https://doi.org/10.1108/JM2-06-2020-0159.

Kim, Young-In, and Hyun-Jung Kim. 2021. "Rescheduling of Unrelated Parallel Machines with Job-Dependent Setup Times under Forecasted Machine Breakdown." *International Journal of Production Research* 59 (17): 5236–5258. https://doi.org/10.1080/00207543.2020.1775910.

Kolomvatsos, Kostas, Kyriaki Panagidi, Ioannis Neokosmidis, Dimitris Varoutas, and Stathes Hadjiefthymiades. 2016. "Automated Concurrent Negotiations: An Artificial Bee

Colony Approach." *Electronic Commerce Research and Applications* 19 (September): 56–69. https://doi.org/10.1016/j.elerap.2016.09.002

Kumar, Prashant, and Ananda Shankar Hati. 2021. "Review on Machine Learning Algorithm Based Fault Detection in Induction Motors." *Archives of Computational Methods in Engineering* 28 (3): 1929–1940. https://doi.org/10.1007/s11831-020-09446-w.

Kumar, Veepan, Prem Vrat, and Ravi Shankar. 2021. "Prioritization of Strategies to Overcome the Barriers in Industry 4.0: A Hybrid MCDM Approach." *Opsearch* 58 (3): 711–750. https://doi.org/10.1007/s12597-020-00505-1

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.

Lăzăroiu, G., T. Kliestik, and A. Novak. 2021. "Internet of Things Smart Devices, Industrial Artificial Intelligence, and Real-Time Sensor Networks in Sustainable Cyber-Physical Production Systems." *Journal of Self-Governance and Management Economics* 6 (1): 20. https://doi.org/10.22381/jsme9120212.

Lee, Jay, Hossein Davari, Jaskaran Singh, and Vibhor Pandhare. 2018. "Industrial Artificial Intelligence for Industry 4.0-Based Manufacturing Systems." *Manufacturing Letters* 18 (October): 20–23. https://doi.org/10.1016/J.MFGLET.2018.09.002.

Lei, Deming. 2010. "A Genetic Algorithm for Flexible Job Shop Scheduling with Fuzzy Processing Time." *International Journal of Production Research* 48 (10): 2995–3013. https://doi.org/10.1080/00207540902814348.

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

Li, Dan, Chunhong Liu, and Kang Li. 2019. "A Remanufacturing Logistics Network Model Based on Improved Multi-Objective Ant Colony Optimization." *Journal Européen Des Systèmes Automatisés* 52 (4): 391–395. https://doi.org/10.18280/jesa.520409

Li, Qiubo, and Ru Xiao. 2021. "The Use of Data Mining Technology in Agricultural E-Commerce under the Background of 6G Internet of Things Communication." https://doi.org/10.1007/s13198-021-01108-9.

Lolli, F., E. Balugani, A. Ishizaka, R. Gamberini, B. Rimini, and A. Regattieri. 2019. "Machine Learning for Multi-Criteria Inventory Classification Applied to Intermittent Demand." *Production Planning and Control* 30 (1): 76–89. https://doi.org/10.1080/09537287.2018.1525506.

Loske, Dominic, and Matthias Klumpp. 2021. "Human-AI Collaboration in Route Planning: An Empirical Efficiency-Based Analysis in Retail Logistics." *International Journal of Production Economics* 241 (November): 108236. https://doi.org/10.1016/j.ijpe.2021.108236.

Luan, Jing, Zhong Yao, Futao Zhao, and Xin Song. 2019. "A Novel Method to Solve Supplier Selection Problem: Hybrid Algorithm of Genetic Algorithm and Ant Colony Optimization." *Mathematics and Computers in Simulation* 156 (February): 294–309. https://doi.org/10.1016/j.matcom.2018.08.011.

Luo, Bo, Haoting Wang, Hongqi Liu, Bin Li, and Fangyu Peng. 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.

Magaldi, Danielle, and Matthew Berler. 2020. "Semi-Structured Interviews." *Encyclopedia of Personality and Individual Differences*, 4825–4830. https://doi.org/10.1007/978-3-319-24612-3_857

Majumdar, Abhijit, Himanshu Garg, and Rohan Jain. 2021. "Managing the Barriers of Industry 4.0 Adoption and Implementation in Textile and Clothing Industry: Interpretive Structural Model and Triple Helix Framework." *Computers in Industry* 125: 103372. https://doi.org/10.1016/j.compind.2020.103372

Mani, Annapoorni, Shahriman Abu Bakar, Pranesh Krishnan, and Sazali Yaacob. 2021. "Categorization of Material Quality Using a Model-Free Reinforcement Learning Algorithm." *Journal of Physics: Conference Series* 2107 (1): 012027. https://doi.org/10.1088/1742-6596/2107/1/012027.

Manimuthu, Arunmozhi, V. G. Venkatesh, V. Raja Sreedharan, and Venkatesh Mani. 2021. "Modelling and Analysis of Artificial Intelligence for Commercial Vehicle Assembly Process in VUCA World: A Case Study." *International Journal of Production Research* April: 1–19. https://doi.org/10.1080/00207543.2021.1910361.

Miles, Matthew B., and A. Michael Huberman. 1994. *Qualitative Data Analyses: An Expanded Sourcebook*. 2nd ed. Thousand Oaks, CA: SAGE Publications.

Mohapatra, P., Lyes Benyoucef, and M. K. Tiwari. 2013. "Realising Process Planning and Scheduling Integration Through Adaptive Setup Planning." *International Journal of Production Research* 51 (8): 2301–2323. https://doi.org/10.1080/00207543.2012.715770.

Naz, Farheen, Rohit Agrawal, Anil Kumar, Angappa Gunasekaran, Abhijit Majumdar, and Sunil Luthra. 2022. "Reviewing the Applications of Artificial Intelligence in Sustainable Supply Chains: Exploring Research Propositions for Future directions." *Business Strategy and the Environment* 31 (5): 2400–2423. https://doi.org/10.1002/bse.3034.

Nikseresht, Ali, Bahman Hajipour, Nima Pishva, and Hossein Abbasian Mohammadi. 2022. "Using Artificial Intelligence to Make Sustainable Development Decisions Considering VUCA: A Systematic Literature Review and Bibliometric Analysis." *Environmental Science and Pollution Research* 29 (28): 42509–42538. https://doi.org/10.1007/s11356-022-19863-y.

Nimawat, Dheeraj, and B. D. Gidwani. 2021. "Identification of Cause and Effect Relationships among Barriers of Industry 4.0 Using Decision-Making Trial and Evaluation Laboratory Method." *Benchmarking: An International Journal* 28 (8): 2407–2431. https://doi.org/10.1108/BIJ-08-2020-0429.

Noman, Abdulla All, Umma Habiba Akter, Tahmid Hasan Pranto, and A. K. M. Bahalul. 2022. "Machine Learning and Artificial Intelligence in Circular Economy: A Bibliometric Analysis and Systematic." *Annals of Emerging Technologies in Computing (AETiC)* 6 (2): 13–40. https://doi.org/10.33166/AETiC.2022.02.002.

Nowak, Maciek, Mike Hewitt, and Chelsea C. White. 2012. "Precedence Constrained Pickup and Delivery with Split

Loads." *International Journal of Logistics Research and Applications* 15 (1): 1–14. https://doi.org/10.1080/13675567.2012.660476.

Olan, Femi, Shaofeng Liu, Jana Suklan, Uchitha Jayawickrama, and Emmanuel Ogiemwonyi Arakpogun. 2022. "The Role of Artificial Intelligence Networks in Sustainable Supply Chain Finance for Food and Drink Industry." *International Journal of Production Research* 60 (14): 4418–4433. https://doi.org/10.1080/00207543.2021.1915510.

Omwando, Thomas A, Wilkistar A Otieno, Sajjad Farahani, and Anthony D Ross. 2018. "A Bi-Level Fuzzy Analytical Decision Support Tool for Assessing Product Remanufacturability." *Journal of Cleaner Production* 174: 1534–1549. https://doi.org/10.1016/j.jclepro.2017.11.050

Osterrieder, Philipp, Lukas Budde, and Thomas Friedli. 2020. "The Smart Factory as a Key Construct of Industry 4.0: A Systematic Literature Review." *International Journal of Production Economics* 221: 107476. https://doi.org/10.1016/j.ijpe.2019.08.011

Pasi, Bhaveshkumar N, Subhash K Mahajan, and Santosh B Rane. 2020. "Smart Supply Chain Management: A Perspective of Industry 4.0." *Supply Chain Management* 29 (5): 3016–3030.

Patton, Michael Quinn. 2002. "Two Decades of Developments in Qualitative Inquiry." *Qualitative Social Work* 1 (3): 261–283. https://doi.org/10.1177/1473325002001003636.

Pournader, Mehrdokht, Hadi Ghaderi, Amir Hassanzadegan, and Behnam Fahimnia. 2021. "Artificial Intelligence Applications in Supply Chain Management." *International Journal of Production Economics* 241 (July): 108250. https://doi.org/10.1016/j.ijpe.2021.108250.

Pozzi, Rossella, Tommaso Rossi, and Raffaele Secchi. 2021. "Industry 4.0 Technologies: Critical Success Factors for Implementation and Improvements in Manufacturing Companies." *Production Planning & Control* 34 (2): 139–158. https://doi.org/10.1080/09537287.2021.1891481.

Priore, Paolo, Borja Ponte, Rafael Rosillo, 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://doi.org/10.1080/00207543.2018.1552369.

Priyadarshi, Rahul, Akash Panigrahi, Srikanta Routroy, and Girish Kant Garg. 2019. "Demand Forecasting at Retail Stage for Selected Vegetables: A Performance Analysis." *Journal of Modelling in Management* 14 (4): 1042–1063. https://doi.org/10.1108/JM2-11-2018-0192.

Raj, Alok, Gourav Dwivedi, Ankit Sharma, Ana Beatriz Lopes de Sousa Jabbour, and Sonu Rajak. 2020. "Barriers to the Adoption of Industry 4.0 Technologies in the Manufacturing Sector: An Inter-Country Comparative Perspective." *International Journal of Production Economics* 224: 107546. https://doi.org/10.1016/j.ijpe.2019.107546

Riahi, Youssra, Tarik Saikouk, Angappa Gunasekaran, and Ismail Badraoui. 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

Ruslin, Ruslin, Saepudin Mashuri, Muhammad Sarib Abdul Rasak, Firdiansyah Alhabsyi, and Hijrah Syam. 2022. "Semi-Structured Interview: A Methodological Reflection on the Development of a Qualitative Research Instrument in Educational Studies." *IOSR Journal of Research & Method in Education (IOSR-JRME)* 12 (1): 22–29. https://doi.org/10.9790/7388-1201052229.

Sharma, Ajit. 2023. "Making Electric Vehicle Batteries Safer Through Better Inspection Using Artificial Intelligence and Cobots." *International Journal of Production Research*, 1–20. https://doi.org/10.1080/00207543.2023.2180308

Sharma, Rohit, Anjali Shishodia, Angappa Gunasekaran, Hokey Min, and Ziaul Haque Munim. 2022. "The Role of Artificial Intelligence in Supply Chain Management: Mapping the Territory." *International Journal of Production Research*, https://doi.org/10.1080/00207543.2022.2029611.

Sharma, Sugandha, and Gunwant Singh. 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://doi.org/10.1109/ICMNWC52512.2021.9688530.

Shumanov, Michael, and Lester Johnson. 2021. "Making Conversations with Chatbots More Personalized." *Computers in Human Behavior* 117 (April): 106627. https://doi.org/10.1016/j.chb.2020.106627.

Singh, Lakhwinder Pal, and Ravi Teja Challa. 2016. "Integrated Forecasting Using the Discrete Wavelet Theory and Artificial Intelligence Techniques to Reduce the Bullwhip Effect in a Supply Chain." *Global Journal of Flexible Systems Management* 17 (2): 157–169. https://doi.org/10.1007/s40171-015-0115-z

Slack, Nigel, Stuart Chambers, and Robert Johnston. 2010. *Operations Management*. Harlow, England: Pearson education.

Stentoft, Jan, Kent Adsbøll Wickstrøm, Kristian Philipsen, and Anders Haug. 2021. "Drivers and Barriers for Industry 4.0 Readiness and Practice: Empirical Evidence from Small and Medium-Sized Manufacturers." *Production Planning & Control* 32 (10): 811–828. https://doi.org/10.1080/09537287.2020.1768318

Strategic Program on Artificial Intelligence. 2022–2024. Jointly developed by the The Ministry of Education, University and Research, the Ministry of Economic Development, and the Minister of Technological Innovation and Digital Transition (2021). https://assets.innovazione.gov.it/1637777513-strategic-program-aiweb.pdf.

Stuart, I., D. McCutcheon, R. Handfield, R. McLachlin, and D. Samson. 2002. "Effective Case Research in Operations Management: A Process Perspective." *Journal of Operations Management*, https://doi.org/10.1016/S0272-6963(02)00022-0.

Svoboda, Josef, and Stefan Minner. 2022. "Tailoring Inventory Classification to Industry Applications: The Benefits of Understandable Machine Learning." *International Journal of Production Research* 60 (1): 388–401. https://doi.org/10.1080/00207543.2021.1959078.

Tirkolaee, Erfan Babaee, Saeid Sadeghi, 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, Reza, Vahid Sohrabpour, Ali Nazarpour, Pejvak Oghazi, and Maria Fischl. 2021. "Artificial Intelligence in Supply Chain Management: A Systematic Literature

Review." *Journal of Business Research* 122 (January): 502–517. https://doi.org/10.1016/j.jbusres.2020.09.009.

Tutun, Salih, Ali Tosyali, Hossein Sangrody, Mohammad Khasawneh, Marina Johnson, Abdullah Albizri, and Antoine Harfouche. 2022. "Artificial Intelligence in Energy Industry: Forecasting Electricity Consumption Through Cohort Intelligence & Adaptive Neural Fuzzy Inference System." *Journal of Business Analytics. Taylor & Francis* 6 (1): 59–76. https://doi.org/10.1080/2573234X.2022.2046514.

Unajan, Magdalene 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, Javier, Daniel Schmidt, 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." https://doi.org/10.3390/s19183987.

Voss, Chris, Mark Johnson, and Jan Godsell. 2016. "5 Case Research." *Research Methods for Operations Management*. Routledge, 165.

Voss, Chris, Nikos Tsikriktsis, and Mark Frohlich. 2002. "Case Research in Operations Management." *International Journal of Operations & Production Management* 22 (2): 195–219. https://doi.org/10.1108/01443570210414329.

Wilson, Matthew, Jeannette Paschen, and Leyland Pitt. 2021. "The Circular Economy Meets Artificial Intelligence (AI): Understanding the Opportunities of AI for Reverse Logistics." *Management of Environmental Quality: An International Journal* 33 (1): 9–25. https://doi.org/10.1108/MEQ-10-2020-0222.

Wong, Lai-Wan, Garry Wei-Han Tan, Keng-Boon Ooi, Binshan Lin, and Yogesh K. Dwivedi. 2022. ""Artificial Intelligence-Driven Risk Management for Enhancing Supply Chain Agility: A Deep-Learning-Based Dual-Stage PLS-SEM-ANN Analysis." *International Journal of Production Research*, 1–21. https://doi.org/10.1080/00207543.2022.2063089.

Woschank, Manuel, Erwin Rauch, and Helmut Zsifkovits. 2020. "A Review of Further Directions for Artificial Intelligence, Machine Learning, and Deep Learning in Smart Logistics." *Sustainability* 12 (9): 3760. https://doi.org/10.3390/su12093760.

Wu, Cheng-Hung, Fang-Yi Zhou, Chi-Kang Tsai, Cheng-Juei Yu, and Stéphane Dauzère-Pérès. 2020. "A Deep Learning Approach for the Dynamic Dispatching of Unreliable Machines in Re-Entrant Production Systems." *International Journal of Production Research* 58 (9): 2822–2840. https://doi.org/10.1080/00207543.2020.1727041.

Wuest, Thorsten, Christopher Irgens, and Klaus-Dieter Thoben. 2014. "An Approach to Monitoring Quality in Manufacturing Using Supervised Machine Learning on Product State Data." *Journal of Intelligent Manufacturing* 25 (5): 1167–1180. https://doi.org/10.1007/s10845-013-0761-y

Yeh, Wei Chang, and Mei Chi Chuang. 2011. "Using Multi-Objective Genetic Algorithm for Partner Selection in Green Supply Chain Problems." *Expert Systems with Applications* 38 (4): 4244–4253. https://doi.org/10.1016/j.eswa.2010.09.091.

Yin, R. K. 2009. *Case Study Research: Design and Methods*. 4th ed. Thousand Oaks, CA: SAGE.

Yin, Robert K.. 2018. *Case Study Research and Applications: Design and Methods*. 6th ed. Thousand Oaks, CA: Sage.

Zdravković, Milan, 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.

Zeba, Gordana, Marina Dabic, Mirjana Cicak, and Tugrul Daim. 2020. "Artificial Intelligence in Manufacturing: Bibliometric and Content Analysis." *2020 IEEE / ITU International Conference on Artificial Intelligence for Good, AI4G 2020*, 95–100. https://doi.org/10.1109/AI4G50087.2020.9311087.

Zhang, Hao, and Yan Cui. 2019. "A Model Combining a Bayesian Network with a Modified Genetic Algorithm for Green Supplier Selection." *Modeling and Simulation International* 95 (12): 1165–1183. https://doi.org/10.1177/0037549719826306.

Zhao, Xueqing, 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-12-2019-0188.

Appendix 1: case study protocol

Source 1. Face-to-face interview	
General questions	Company introduction (turnover, employees, sector, product portfolio, business model) Interviewee/s introduction (role in the company, main interests, experience)
AI applications	What are the Artificial Intelligence (AI) applications implemented by your company?
AI and SCOR model	• How do AI applications support each of the following supply chain and operations management processes? • Plan: processes aimed at gathering requirements and information on available resources, balancing requirements and resources to determine planned capabilities and gaps in demand or resources, and identifying actions to correct these gaps • Source: processes aimed at issuing purchase orders, scheduling deliveries, receiving orders, validating orders, storing goods, and accepting suppliers' invoices' • Make: processes aimed at processing, maintenance, repair, overhaul, recycling, refurbishment, manufacturing and other common types of material-conversion processes • Deliver: processes aimed at receiving, validating, and creating customer orders, scheduling order deliveries, picking, packing and shipping, and invoicing customers • Return: processes aimed at moving material from a customer back through the supply chain to address product defects, ordering, or manufacturing, or to perform upkeep activities
Benefits and Barriers	What benefits have been achieved in implementing and adopting AI applications in the above-mentioned processes? How many and what barriers have been encountered in implementing and adopting the AI applications in the above-mentioned processes?
Source 2. Direct observations and internal documents	
Company tour	Direct observation of the AI applications, with the possibility to ask further questions to the employees and/or managers involved.
Digital or paper materials	Internal documents related to the AI projects, with the possibility to ask further questions to the employees and/or managers involved
Source 3. Official documents	
Company's website	General company information; product catalogues and information brochures related to the solutions provided by the companies.
News and press	Up-to-date news related to the companies and their AI applications.
National database	Economic reports and balance sheets.