

On the use of machine learning in supply chain management: a systematic review

M.Z. BABAI[†]

Kedge Business School, Talence, 33400, France

[†]Corresponding author: Email: mohamed-zied.babai@kedgebs.com

M. ARAMPATZIS

Aristotle University of Thessaloniki, Thessaloniki, 54124, Greece

M. HASNI

Ecole Nationale d'Ingenieurs de Bizerte, Bizerte, 7035, Tunisia

F. LOLLI

University of Modena and Reggio Emilia, Reggio Emilia, 42100, Italy

AND

A. TSADIRAS

Aristotle University of Thessaloniki, Thessaloniki, 54124, Greece

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Machine learning (ML) has evolved into a crucial tool in supply chain management, effectively addressing the complexities associated with decision-making by leveraging available data. The utilization of ML has markedly surged in recent years, extending its influence across various supply chain operations, ranging from procurement to product distribution. In this paper, based on a systematic search, we provide a comprehensive literature review of the research dealing with the use of ML in supply chain management. We present the major contributions to the literature by classifying them into five classes using the five processes of the supply chain operations reference framework. We demonstrate that the applications of ML in supply chain management have significantly increased in both trend and diversity over recent years, with substantial expansion since 2019. The review also reveals that demand forecasting has attracted most of the applications followed by inventory management and transportation. The paper enables to identify the research gaps in the literature and provides some avenues for further research.

Keywords: machine learning; supply chain; operations; sustainability; risk management.

1. Introduction

1.1. Context of the study

Supply chain management (SCM) emerges as an important function within companies, driving the efficient management of flows of goods, information and resources from suppliers to customers. Over the time, SCM has evolved into a multifaceted challenge by addressing the ever-increasing complexity of supply chains (Akin Ateş *et al.*, 2022; Chatha & Jalil, 2022). Relevant examples that emphasize such

complexity are related to the products portfolios which are becoming more diverse, as companies now manage a wide range of products with varying characteristics, demand patterns and shelf lives (Han & Chen, 2021; Jalali & Menezes, 2024). The variability of customers' demand could also be perceived as an important influencing factor to the faced complexity. Indeed, promotions, the availability of competitive products as well as exposure to external events such as natural disasters significantly affect customer behaviours (Scholten *et al.*, 2020).

Such complexity also relates to supply chains that involve numerous suppliers, each with its own lead times, quality standards and reliability. The complexity is also linked to various risks including geopolitical instability, natural disasters, economic fluctuations and supply disruptions (Katsaliaki *et al.*, 2022; Chen & Chen, 2023). Furthermore, in the new era of digitization and with the development of new information technologies, considerable amounts of data become available within supply chains from various sources, including sensors, IoT devices, and transaction records and for most of the operations, including procurement, production, inventory, transportation and sales (Talwar *et al.*, 2021). These data can also be obtained in real time.

Within this context of increasing supply chain complexity and data availability, machine learning (ML), a subset of artificial intelligence (AI), has been developed over the last decades to assist supply chain practitioners and researchers in improving their optimization and decision-making (Georgiev *et al.*, 2024; Sanders, 2024). These tools appear as alternative solutions to undertake observed shortages encountered by the available traditional analytical methods (Jahani *et al.*, 2023). In fact, ML tools are shown to effectively capture complex and non-linear relationship within data and hence provide more accurate predictions and informed decisions.

The increasing progress and widespread adoption of ML in SCM have motivated us to conduct a comprehensive review. Our objective is to emphasize the current applications and challenges that are associated with this technology. More specifically, we examine the impact of ML techniques, including its three categories: supervised learning, unsupervised learning and reinforcement learning (RL), on enhancing supply chain efficiency and decision-making processes.

1.2. Previous review papers

The application of ML in SCM has attracted several review papers in the literature. Ni *et al.* (2020) analyzed the literature published between 1998 and 2018. The review search was based on two keywords 'supply chain management' and 'machine learning' and has identified 123 articles. The findings of the work showed the trends of the research, the most used ML algorithms and the distribution of ML algorithms in SCM activities, including storage, inventory, transportation and distribution. Akbari & Do (2021) used a systematic literature review (SLR) to identify the trends and research directions with regard to the use of ML in logistics and SCM. The SLR was conducted between 1994 and 2019 using the keywords 'Machine Learning', 'Logistics', 'Transportation' and 'Supply Chain' and has identified 110 articles. They showed the statistical trends of ML in SCM along with some challenges without showing the findings of the literature with regard to the ML techniques that are used or the SCM applications. Toorajipour *et al.* (2021) conducted an SLR of the literature spanning between 2008 and 2018 with the keywords 'supply chain', 'production', 'marketing' and 'logistics'. The search resulted in 64 papers that were analyzed by the authors, focusing on the AI techniques used in the reviewed papers. Mendonça & Junior (2023) conducted a review of 40 papers between 2000 and 2020. Their SLR was based on general keywords such as AI, ML, Expert Systems and SCM. They analyzed the papers considering the main areas of the supply chain operations reference (SCOR) model framework of operations to identify the main research methodologies used in the literature and the main applications of AI in SCM operations.

However, it should be noted that all of these published SLRs have reviewed papers until 2020, whereas in the last 3 years, the field has moved on rapidly, particularly with regard to some ML techniques, such as RL techniques, and SCM applications. Moreover, none of the above reviews has analyzed the literature dealing with specific processes in SCM such as procurement, inventory management, maintenance, etc.

In the recent years, some other systematic reviews have also been published. These reviews have been dedicated to analyze the research in specific sectors, such as the agriculture (Sharma *et al.*, 2020; Gupta *et al.*, 2023; Kumari *et al.*, 2023), the retail (Gopal *et al.*, 2024), etc., or to deal with specific SCM processes, such as demand forecasting (Hassan, 2022; Gautam *et al.*, 2023), inventory management (Sadowski *et al.*, 2023), maintenance (Ma *et al.*, 2022); transportation (Deniz & Özceylan, 2023), or to deal with a specific ML technique used in SC applications, such as RL (Yan *et al.*, 2022; Rolf *et al.*, 2023). However, there is a recent SLR that is relevant to our review paper, which is conducted by Jahani *et al.* (2023). The authors analyzed the literature dealing with the use of data science and big data analytics (DS and DBA) including ML in SCM. Their review is based on a sample of 364 papers published between 2005 and August 2022. In their analysis, they looked at short, mid-term and long-term decisions in supply chain processes including procurement, production, distribution, logistics and sales. They also analyzed 16 review papers published in A and Q1 journals. Their analysis missed though some supply chain processes, such as demand forecasting and maintenance.

1.3. *Contribution and structure of the paper*

By analyzing the previous published SLRs dealing with the applications of ML in SCM, we have identified two main limitations: (1) most of the previous SLRs have reviewed papers published until 2020, whereas in the last 3 years, the field has moved on rapidly, particularly with regard to some ML techniques and the SCM processes; (2) there are few recent systematic reviews that have covered the literature published until 2022; however, they have been dedicated to analyze only specific sectors or specific supply chain processes, lacking important ones, such as demand forecasting, inventory management and maintenance. Bridging this gap in the literature, constitutes the objective of our paper. The review conducted in this paper covers the developments published until the end of 2023. Moreover, it is based on a search ontology that covers the keywords used in previous SLRs in addition to a set of new keywords, related to SCM and ML concepts that have been recently considered in the literature. Hence, based on 415 identified papers published between 2000 and 2023, we provide in this paper a comprehensive literature review of the most updated research dealing with the applications of ML in SCM. We have reviewed the major contributions to the literature by classifying them into five classes, based on the five supply chain processes defined by the SCOR model: *PLAN*, *SOURCE*, *MAKE*, *DELIVER* and *RETURN* (Ntobe *et al.*, 2015). In the *PLAN* process, we have included all publications dealing with the demand forecasting and inventory management decisions. The procurement applications are included in the *SOURCE* process. We have included production decisions and the maintenance of production systems in the *MAKE* process whereas the distribution and transportation decisions are in the *DELIVER* process. In the *RETURN* process, sustainability applications using return flows are considered. The methodology used to identify the classes and to evaluate their content is based on the procedure presented in Seuring & Müller (2008), which consists in using a deductive approach to select beforehand the classes to be analyzed for the review.

The remainder of this paper is organized as follows. Section 2 describes the methodology used to conduct the systematic review. The statistical analysis of the identified papers is provided in Section 3, accompanied by an analysis of the trends of the research contributions. Section 4 reviews the findings of the literature that deals with the applications of ML in SCM by splitting this literature into five

classes defined by the SCOR model. Section 5 presents the conclusions of the work and identifies the research gaps.

2. Review methodology

We performed a systematic review of the literature to (i) identify all published SCM articles that have considered ML techniques; (ii) evaluate their contribution to the literature; and (iii) summarize their findings, strengths and limitations.

The Scopus electronic database was used to search for all articles published between 2000 and 2023. Scopus is selected because it is characterized by its broad coverage of journals in management and engineering sciences (Sgarbossa *et al.*, 2023). We used a keyword search structure composed of two groups. The first group consists of the keywords related to the SCM context, whereas the second group consists of the keywords that relate to the ML context. We performed a two-step search procedure. In the first step, we considered straightforward keywords related to the supply chain and its three main structural processes, also based on previous SLRs, i.e., ‘supply chain’, ‘procurement’, ‘production’ and ‘distribution’ and for the ML context, we used the simple keyword ‘machine learning’. For the latter, only ‘machine learning’ was initially used and we did not use keywords related to the general areas of AI and generative AI (GAI) since they lead to a broad literature that is beyond the scope of our review paper. However, we noticed that the first search did not include the literature related to some supply chain processes, despite the fact that they have attracted a considerable part of the literature, such as ‘demand forecasting’, ‘inventory management’, ‘transportation’ and ‘maintenance’, and some specific ML techniques/categories, such ‘supervised learning’, ‘unsupervised learning’ and ‘reinforcement learning’. Thus, we have conducted a second search where we have specified a larger set of keywords covering the missing supply chain processes and ML categories according to the authors’ knowledge in these areas. Note that this search ontology was restricted to the title, or keywords, or abstract. Hence, the following search ontology was finally used: ‘[”supply chain” OR ”procurement” OR ”production” OR ”distribution” OR ”demand forecasting*” OR ”inventory management” OR ”transportation” OR ”maintenance”]’ AND ‘[”machine learning” OR ”supervised learning” OR ”unsupervised learning” OR ”reinforcement learning”]’.

As shown in Fig. 1, the application of the two-step search ontology yielded initially to 98225 documents. We screened the documents to include only documents that are published in English between 2000 and 2023 as articles, books, reviews or book chapters, which resulted in 45764. We also excluded documents that do not belong to the category of ‘Business, Management and Accounting’ or ‘Decision Sciences’, which resulted in 3090 documents. In the following step, we only kept the documents published in operations and/or SCM or operations research journals, which resulted in 1131 documents. The step of eligibility consists in checking the titles and abstracts of the documents to ensure that the topic relates to SCM. The documents were split between the authors to check the eligibility and this step yielded the exclusion of 411 records. Hence, the final sample used for the review is composed of 720 documents. It is worth pointing out that within the final sample, we have noticed that there are many documents that, although they cite ML within the SCM literature, they do not include a particular ML technique or an SCM application such as review papers, which makes them less interesting for our analysis conducted in Section 4 of this paper. Therefore, our final review is based on 415 papers, which have been thoroughly analyzed in this paper.

To report the findings of our review, we first conducted a descriptive analysis to show some statistics related to the final sample of papers along with some general information and trend of the published papers. We then reviewed the contributions of the literature by following a procedure presented in

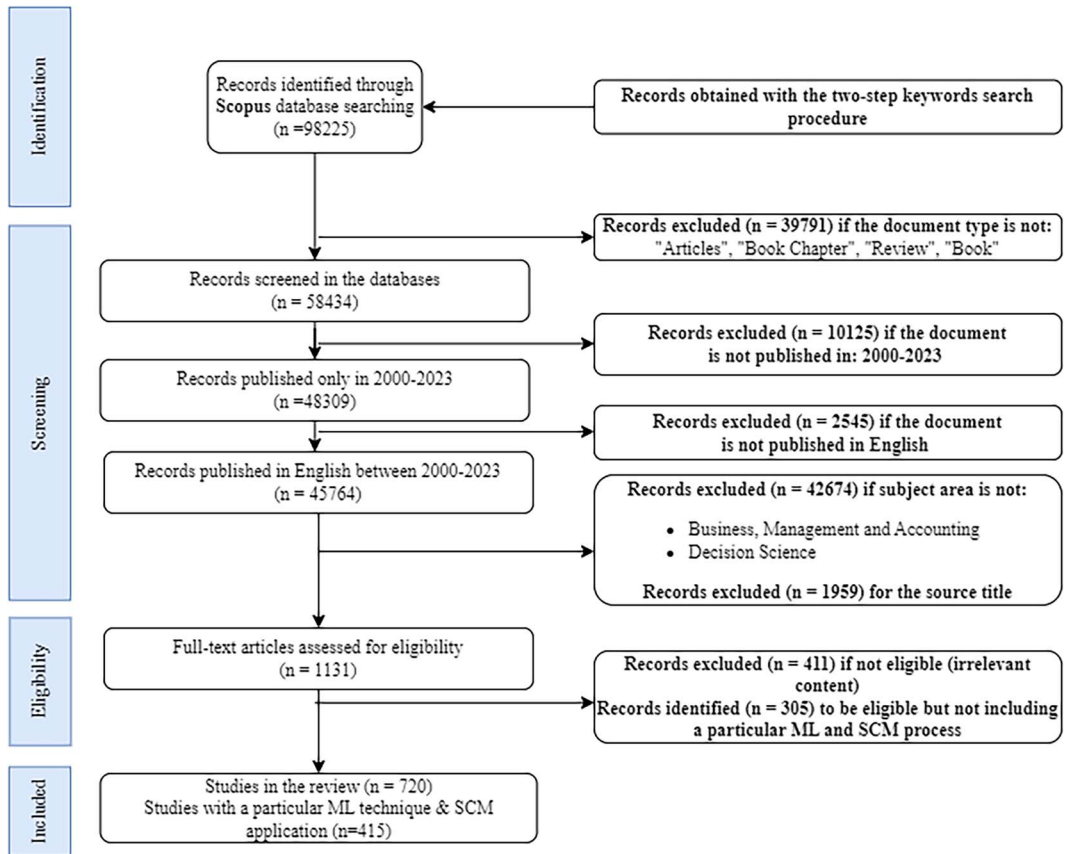


FIG. 1. Systematic review search methodology.

Seuring & Müller (2008) and Sgarbossa *et al.* (2023). This procedure shows that from a methodological point of view, a literature review can be comprehended as a content analysis, where quantitative and qualitative aspects are mixed to assess structural as well as content criteria. Hence, we used structural dimensions, i.e., selected categories, to evaluate the content material collected for the review. For the selection of the categories, we used a deductive approach, which consists in classifying the contributions, before the literature is analyzed, using the SCOR theoretical framework. In fact, we classified the contributions into five classes, based on the five supply chain processes (plan, source, make, deliver and return) as defined in the SCOR framework.

3. Statistical analysis and trends of research contributions

In this section we analyze the general trend of the publications dealing with ML applications in SCM. We also present the trend and statistics related to these publications per source title, learning type considered in the research work and the supply chain process.

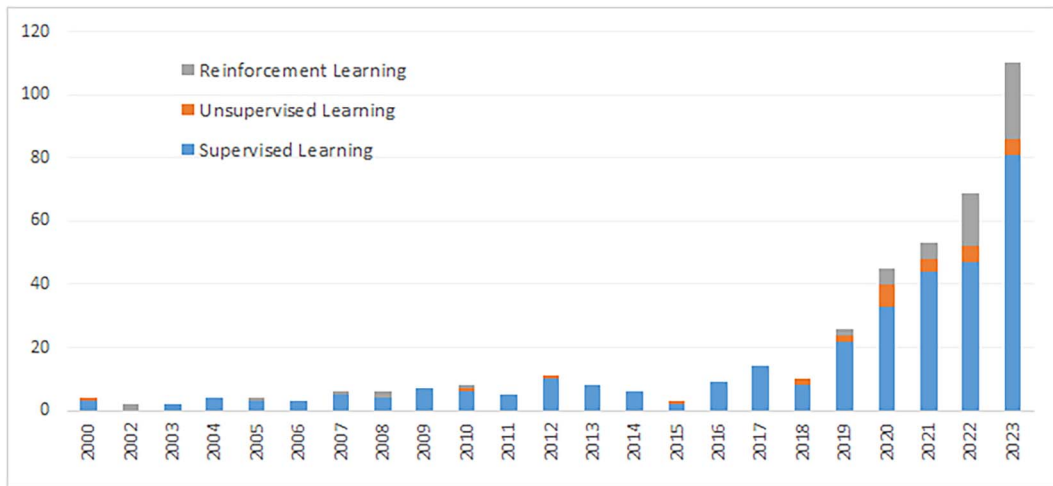


Fig. 2. Evolution of the number of publications per year.

To start with, Fig. 2 depicts the evolution of the number of publications between 2000 and 2023, including those in each of the three ML categories, i.e., supervised learning, unsupervised learning and RL.

The results show that the number of publications, dealing with the application of ML in SCM, was slightly fluctuating but remained relatively stable until 2018. However, Fig. 2 shows that the literature has clearly seen an expansion since 2019 and the number of publications has substantially increased in 2023 compared to 2022. Moreover, the results clearly show that supervised learning is the most used category of ML techniques within the SCM applications with a clear increase in the applications of the RL methods between 2019 and 2023. The applications using unsupervised learning remain comparatively limited. This may be explained by the fact that these models typically intervene in selecting adequate input data for the analysis rather than being central to the core analysis task.

With a view to refine our selection, we focus on the top 15 journals with the highest number of published papers. Figure 3 depicts the number of papers per source title to help highlighting the selected journals.

Figure 3 shows that a considerable part of the research dealing with ML and its applications in SCM has been published in the *International Journal of Production Research* with more than 50 published papers followed by the *International Journal of Production Economics*. Figure 3 also shows that the *International Journal of Forecasting* is among the journals that has not published many papers using ML, despite the fact that the area of demand forecasting, as it will be shown further in the paper, is the area that has attracted most of the applications of ML in the literature. The results of the search also reveal that the research published in the American journals remains limited with only few papers published in journals such as *Management Science* and *Manufacturing and Service Operations Management*.

Figure 4 reports the statistics of the published papers per SCM process and shows the ML category used in each process. We show the statistics by considering the processes being classified into the five SCOR processes and we also report the supply chain areas in each class.

As may be noticed from Fig. 4, the *PLAN* process has attracted most of the research related to ML within the supply chain literature, with about 50% of the publications. It is clear that within this process,

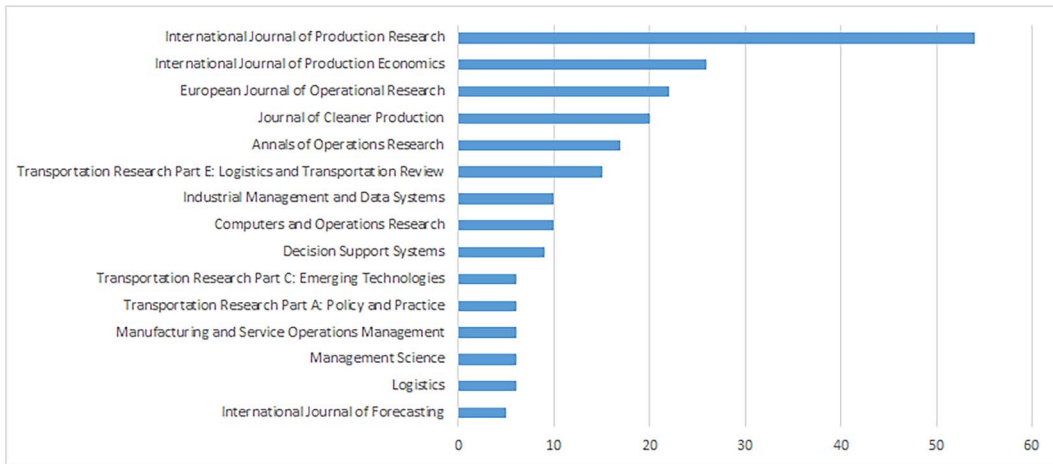


FIG. 3. Number of publications per source title (2000–2023).

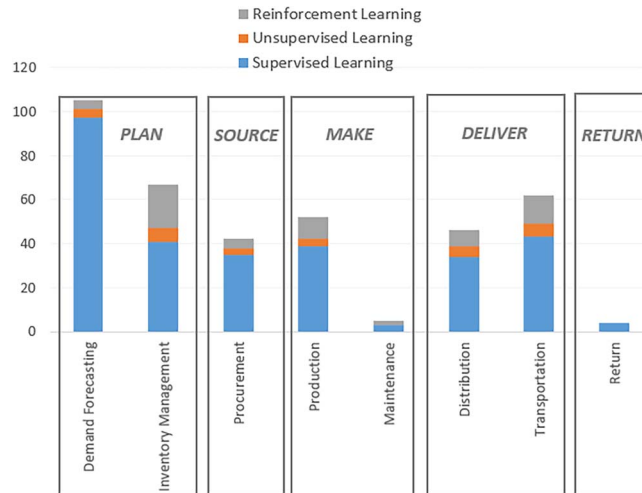


FIG. 4. Number of publications per supply chain application (2000–2023).

‘demand forecasting’ and ‘inventory management’ are the dominating areas. The statistical analysis also shows that the *DELIVER* process is the second most considered process, with both the ‘distribution’ and ‘transportation’ areas reaching 27% of the literature. The *RETURN* process has attracted very little number of publications considering ML. The results also show that supervised learning techniques are the most used in all supply chain processes (exceeding 300 publications in total), whereas the unsupervised learning techniques are the least considered ones (with less than 30 publications in total). It should also be noted that RL is particularly more used in the inventory management publications.

4. Supply chain processes and ML applications

This section reviews the findings of the literature dealing with the use of ML in various SC processes. We present these findings by relating them to the *PLAN*, *SOURCE*, *MAKE*, *DELIVER*, *RETURN* processes in the supply chain.

4.1. *PLAN* process

For this process, we focus on the management and planning decisions within supply chains, including demand forecasting and inventory management.

4.1.1. *Demand forecasting.* Demand forecasting is a vital task in SC management as it affects strategic, tactical and operative decisions (Babai *et al.* 2020), to such an extent that most of the reviewed papers refer to demand forecasting. In particular, the bullwhip effect, one of the most important issues facing multi-echelon SCs, can be mitigated by accurate forecasts (Zhang, 2004), which become more and more vital in these contexts. In order to forecast future demand, the forecasting approaches can use (Yasir *et al.*, 2022):

- Endogenous input data, which refer solely to the time-series of past demands as common inputs of the conventional statistical parametric approaches.
- Exogenous input data (e.g., price fluctuations and customers' behaviours), which affect the demand and thus can be collected and used to extract valuable knowledge from heterogeneous data sources and improve forecasts' accuracy (Lamba & Singh, 2017; Brookes *et al.*, 2024; Debnath *et al.*, 2024; Rostami-Tabar *et al.*, 2024). This justifies the greater attention placed in the last decade on ML for demand forecasting, as ML is the main pillar of big data analytics.
- Hybrid input data when both endogenous and exogenous inputs are used.

One of the first works using only endogenous inputs to train ML approaches is that proposed by Carbonneau *et al.* (2008), where they forecast the demand at the end of the supply chain (distorted demand resulting from the bullwhip effect) by using artificial neural networks (ANN), recurrent neural networks (RNN) and support vector machine (SVM) compared to classical statistical methods (i.e., naïve, moving average and linear regression). Several works exploit the forecasting accuracy of ML approaches in different sectors using only endogenous inputs: automotive sector (e.g., Singh & Challa (2016), Leung *et al.* (2009), Cao & Shen (2019)), medical sector (e.g., Koulouriotis & Mantas (2012), Barros *et al.* (2021), Zhu *et al.* (2021), Rekabi *et al.* (2023)) and food sector (e.g., Singh & Mishra (2023a), Singh & Mishra (2023b)) are examples of application fields of ML approaches using endogenous input. A challenging trans-sectorial field for the application of ML is represented by intermittent demand (Syntetos & Boylan, 2001), which arises in many real industrial contexts such as spare parts, start-up productions, multi-echelon supply chains (Syntetos *et al.*, 2015) as well as when forecasting retail sales at a store or product level (Spiliotis *et al.*, 2020). The works of Gutierrez *et al.* (2008), Kourentzes (2013), Lolli *et al.* (2017), Babai *et al.* (2020), Jiang *et al.* (2021) and Zhang *et al.* (2023) are examples of empirical comparison of ML approaches with parametric methods, in particular Croston's method (Croston, 1972) and the Syntetos–Boylan Approximation (SBA) (Syntetos & Boylan, 2005), when forecasting intermittent demand using only endogenous variables. As underlined in Zhang *et al.* (2023), it deserves to be noted that the higher the intermittence, the more challenging the forecasting is as the number of observations decreases. In order to address this limitation and improve the forecast accuracy, Zhuang *et al.* (2022) explore the use of exogenous input data for forecasting intermittent demand in the

field of automotive spare parts (e.g., retention data of the car type to which the spare part belongs and type of spare part). Indeed, in the last few years, ML is exploited extensively for demand forecasting (not only intermittent) also by including into the input set some exogenous explanatory variables, along with the endogenous inputs coming from the time series. Actually, the explanatory variables advantage ML over standard forecasting techniques as ML is a powerful tool for interpreting Big Data (Boone *et al.*, 2019).

Papers accounting for hybrid inputs deal with several exogenous variables based on the specific sector analyzed, e.g.: Kaya *et al.* (2022) for the automotive sector; Feizabadi (2022) for the steel sector; (Ferreira *et al.*, 2016; Loureiro *et al.*, 2018; Giri & Chen, 2022; Yasir *et al.*, 2022; Fu & Fisher, 2023) in the sector of fashion retail, where many exogenous product-related variables from different data sources (e.g., e-commerce and social media) can improve forecasting accuracy. All the aforementioned contributions on hybrid approaches allow us to underline once again the ability of ML of capturing complex relationships between demand and Big Data. More recently, this feature of ML has been investigated in the famous M5 forecasting competition (Spiliotis *et al.*, 2021), which differently from the previous four editions (Makridakis *et al.*, 1982, 1993; Makridakis & Hibon, 2000; Makridakis *et al.*, 2020) comprehends for the first time not only time series standalone but also exogenous variables. In particular, the interesting finding of M5 competition is that all 50 top performing methods are based on ML (Makridakis *et al.*, 2022). This clearly shows the power of ML in dealing with exogenous variables not included in the previous competitions. Spiliotis *et al.* (2021) exploit the M5 data to forecast probabilistic product sales, i.e. quantiles. They find that no forecasting method outperforms the others across all the considered quantiles. Moreover, they individuate how the added-value brought by more sophisticated methods needs to be evaluated in terms of inventory performance as simple and empirical methods are proved to provide very similar inventory performance at a lower computational cost. In conclusion, no model outperforms the others in all the situations. In other words, there are 'horses for courses', i.e., methods that fit better than others for some types of data (Petropoulos *et al.*, 2014). Nevertheless, ML performs better than statistical methods when exogenous data are included (Makridakis *et al.*, 2022); this justifies the greater attention given to ML during the current Big Data era. It is worth stressing that all the aforementioned papers exploit supervised ML approaches. However, unsupervised ML approaches may be applied to forecasting as a pre-processing stage. For example, Pereira & Frazzon (2021) cluster products of an omni-channel retailer, and Thomassey (2010) uses unsupervised ML approaches for data pre-treatment in the fashion sector.

We summarize in Table 1 the research dealing with ML in the demand forecasting literature using a classification by sector (rather than by SC application since all the publications deal with the demand forecasting application). This summary along with our analysis of the statistics about ML techniques used in the literature reveals that the NN approach clearly dominates the demand forecasting literature. In fact, ANNs and RNNs are particularly highly recommended in demand forecasting due to their proficiency in modeling complex, non-linear relationships and handling time series data patterns. However, for smaller datasets with well-defined demand boundaries, SVMs are more suitable. It should also be noted that in sectors with significant external influences, such as automotive and fashion retail, hybrid models that integrate both endogenous and exogenous data can greatly enhance forecasting accuracy.

Finally, it is worth pointing out that all the reviewed papers related to forecasting deal with either supervised or unsupervised coupled with supervised ML approaches. To the best of our knowledge, only one paper (Hassan *et al.*, 2020) applies an RL approach, where an RL framework combining time series models and ML algorithms is proposed. Specifically, after clustering the dataset, RL is used for learning dynamically the performance of various forecasters based on their past accuracy. Then, the forecasters are weighted period by period to achieve the forecast for the incoming one, according to the specific

TABLE 1. *ML applications in demand forecasting*

SC application & sector	ML method	Reference
Forecasting in the automotive sector	GRNN	Leung <i>et al.</i> (2009)
	DPFNN	Cao & Shen (2019)
Forecasting in the medical sector	ANN, ANFIS	Singh & Challa (2016)
	ANN	Kaya <i>et al.</i> (2022)
	ANN, RNN, ANFIS	Koulouriotis & Mantas (2012)
	RNN	Zhu <i>et al.</i> (2021)
Forecasting in the food sector	ANN, SVR	Barros <i>et al.</i> (2021)
	LR, QR	Rekabi <i>et al.</i> (2023)
	DT	Singh & Mishra (2023a)
Forecasting in the steel sector	DT	Singh & Mishra (2023b)
Forecasting in retail	ARIMAX, ANN	Feizabadi (2022)
	ANN, RF regression, SVM, DTR	Loureiro <i>et al.</i> (2018)
Forecasting intermittent demand	SR, PCR, PLSR, MR, SR, RT	Ferreira <i>et al.</i> (2016)
	ANN, k-means	Pereira & Frazzon (2021)
	DT, k-means	Thomassey (2010)
	CNN, k-means, k-NN, SVM, RF, ANN, NB	Giri & Chen (2022)
	LR, SVR, LSTM, GLSR	Yasir <i>et al.</i> (2022)
	ANN	Fu & Fisher (2023)
	ANN	Gutierrez <i>et al.</i> (2008)
	ANN, ELM	Kourentzes (2013)
	ANN	Lolli <i>et al.</i> (2017)
	AUSVM	Babai <i>et al.</i> (2020)
ANN	Jiang <i>et al.</i> (2021)	
TrAdaBoost	Zhang <i>et al.</i> (2023)	
	Zhuang <i>et al.</i> (2022)	

instance under evaluation. That is to say, RL has the potential benefit to improve the forecasting accuracy through a rolling horizon approach, and thus represents a promising as well as yet poorly researched ML technique in SC management.

4.1.2. *Inventory management.* ML has been used since 2000s for inventory management applications. The contributions in the literature can be categorized in three classes:

- Solving problems that are modelled as a Markov decision process (MDP) with curse of dimensionality.
- Considering big data driven inventory control, i.e., dealing with distribution-free inventory problems.
- Solving inventory classification problems, mainly under a multi-criteria classification context.

Within the first class of contributions, many authors consider the case of multi-echelon stochastic inventory systems. This is justified by the fact that finding optimal or near-optimal solutions in this case implies exponentially large scenario trees, which can be tackled using ML methods. Early works in the literature include [Giannoccaro & Pontrandolfo \(2002\)](#) and [Chaharsooghi *et al.* \(2008\)](#) where RL algorithms are considered to deal with inventory problems and the optimization is determined using an average reward criterion. The solution is obtained by means of a Q-learning algorithm. This literature shows that using the Q-learning algorithm leads to a high reduction of inventory costs compared to classical benchmarks such as genetic algorithms. ANN are also used to deal with inventory problems, especially to represent scenarios' trees, and can lead to near-optimal solutions even using simple networks ([Prestwich *et al.*, 2012](#)). More recently, deep reinforcement learning (DRL), which refers to the inclusion of neural networks in RL, has attracted many researchers in the inventory literature. It has been shown how DRL can also be used as a numerical approach to approximately optimize a large class of inventory problems that are modelled as MDPs with curse of dimensionality. The key design choices of DRL algorithms to facilitate their implementation have also been discussed ([Boute *et al.*, 2022](#)). Naturally, within this literature, the deep Q-network algorithm (DQN) is used ([De Moor *et al.*, 2022](#); [Oroojlooyjadid *et al.*, 2022](#)) and it is applied to the perishable inventory problems and to the beergame. It should be noted that the classic Q-learning algorithm and its advanced versions are the most used RL algorithms in the inventory literature. This may be explained by the fact that the classic Q-learning algorithm consists in finding an optimal policy often by maximizing the expected value of the total reward, which is applied to an MDP using an optimal action-selection policy. Such a process is natural for most of the inventory control problems that consist in finding the optimal policy after modelling it as an MDP. Since the modelling of inventory policies in omnichannel distribution systems using MDPs also lead to curse of dimensionality, RL is used by [Goedhart *et al.* \(2023\)](#) to solve such problems. Other examples of applications of ML where data are used to prescribe optimal decisions in inventory control problems in other contexts (e.g., omnichannel inventory system, advanced inventory policies, etc.) can be found in [Bertsimas & Kallus \(2020\)](#); [Asadi & Pinkley \(2021\)](#); [Chen *et al.* \(2022\)](#); [Gijsbrechts *et al.* \(2022\)](#); [Preil & Krapp \(2022\)](#); [Wang *et al.* \(2022\)](#); [Bertsimas *et al.* \(2023\)](#); [Park *et al.* \(2023\)](#).

With regard to the second class of contributions, a considerable body of research deals with big data driven inventory problems ([Ban & Rudin, 2019](#); [Huber *et al.*, 2019](#); [Clausen & Li, 2022](#); [Neghab *et al.*, 2022](#); [Tian & Zhang, 2023](#)). The main idea of this literature is that the models relax the distribution assumptions of the demand and they are solved using ML methods based on real observed data. A work where the newsvendor model is considered has been introduced by [Ban & Rudin \(2019\)](#) and an extension by [Clausen & Li \(2022\)](#) has been developed in the case of an order-up-to level model. Algorithms based on ANNs and kernel-weights optimization have been used to solve the problems, which allows to empirically show the importance of the consideration of features within the data in solving free-distribution inventory problems. [Galli *et al.* \(2021\)](#) is another example of a research where the authors considered the K-NN, DT and RF methods to solve a distribution-free inventory problem using real data in a healthcare context. In another stream of literature, it has been shown that ML can be used to select an appropriate inventory strategy among different strategies while avoiding time consuming simulations (e.g., [Tsai & Huang \(2012\)](#)). To cite some of this research, [Faccio \(2015\)](#) showed the performance of a heuristic procedure based on a DT approach in identifying the most appropriate warehouse centralization/decentralization strategy for spare parts. More recently, the literature has shown how the time of simulation can be reduced when using deep neural networks ([Van der Gaast & Weidinger, 2022](#)).

Within the third class of contributions, the objective of the research is to propose methods that classify items based on their inventory performance (i.e., jointly carrying the tasks of inventory classification and

TABLE 2. *Inventory control applications of ML*

SC application	ML method	Reference
Inventory problems modelled as an MDP with curse of dimensionality	RL	Giannoccaro & Pontrandolfo (2002), Chaharsooghi <i>et al.</i> (2008), Bertsimas & Kallus (2020), Boute <i>et al.</i> (2022)
Big data driven inventory problems (distribution free inventory problems)	NN KNN, DT and RF	Clausen & Li (2022) Galli <i>et al.</i> (2021)
Inventory classification problems	DT SVM ML classifiers with a GA	Faccio (2015) Lolli <i>et al.</i> (2019) Svoboda & Minner (2022)

control) instead of separately classifying items and finding appropriate control policies for the classes. In this line of research, a multi-criteria inventory classification problem when items have an intermittent demand pattern has been solved by Lolli *et al.* (2019) using methods such as SVM with a Gaussian kernel and deep neural networks. This research has provided evidence on the reduction of the simulation efforts and the high classification accuracy. Another more recent example, the work of Svoboda & Minner (2022) where an ML-based inventory classification method is proposed enabling to assign products to classes of inventory control policies having specific target service levels and demand distributions. In addition to the ML classifiers, GA is considered to train cost-minimizing DTs. The authors show that the proposed method provides classifications that have an average cost close to the cost-optimal classifications.

We present in Table 2 the three categories of applications in the inventory control literature using ML along with the used techniques and key references.

4.2. SOURCE process

Supplies are a critical point in supply chains, and due to their complexity, the use of modern methods such as ML is required. In this field, especially since 2020, there has been a continuously increasing number of published papers.

There are studies (e.g., Ali *et al.* (2023b)) where criteria that each organization must consider for partner selection have been identified and proposed using the RF method. Other studies (e.g., Pal *et al.* (2017)) have found, through the application of LR and NNs, that the factors for selecting an appropriate partner are as follows: service provided by suppliers and/or subcontractors, continuous improvement, supplier and/or subcontractor delivery reliability, and effective problem-solving. Furthermore, using ANN (Kuo *et al.*, 2010; Manohar & Kumar, 2020), ecological parameters for the corresponding issue have been evaluated.

Additionally, the collaboration between businesses or entities has often been studied either in advance or retrospectively, meaning either for selecting a partner or for evaluating the existing collaboration and the possibility of its termination. This has been done using various ML algorithms such as DT, RF, GBM (Abdulla *et al.*, 2023), ANN (Akbaba & Çetin, 2022) and RL methods (Kim *et al.*, 2008). Research has also been conducted on creating a ranking series of suppliers according to the priorities of the business, once again using ANN (Sharma & George, 2021).

Deciding what to perform in-house and what to hire outside providers to do is a crucial and vital decision for businesses. The decision to collaborate with third-party logistics (3PL) service providers offers flexibility but also raises issues such as information sharing for the businesses that choose it. For example, ANN has been used to evaluate options so that the interested business can decide whether or not to seek a 3PL partner (Raut *et al.*, 2017). Research has also been done on issues related to supplier selection exclusively in agile supply chains (Wu & Barnes, 2012). According to it, and after using various methods including ANNs, practitioners may find it difficult to match supplier evaluation criteria with the strategic objectives for an agile supply chain, and they may perceive the model to be too complex for use when speed is of the essence.

One of the few cases of using RL in the field of procurement is the study of consumer behaviour and the influence of supplier pricing on the retailer's competitiveness (Deng, 2023).

The optimal way of exchanging information and data between partners constitutes a competitive advantage for businesses that implement it, although there are risks associated with such a move. The exchange of information regarding procurement costs significantly contributes to this. The use of ANN has emerged as the most effective way of supporting the sharing of strategic information in buyer–supplier relationships and reducing the manual effort for data preparation (Bodendorf *et al.*, 2022).

Besides partners, each business is also influenced by the actions of competitors, which, due to the lack of information exchange, is naturally difficult to study. Despite the difficulty, Mamoudan *et al.* (2022) attempted this in 2022. Using advanced ML methods such as convolutional neural network (CNN) and long short-term memory (LSTM), they managed to predict future prices of competitive brands, allowing the studied business to manage this information to its advantage.

The main areas of application of ML in the procurement literature, the ML techniques used and the key references are summarized in Table 3.

4.3. MAKE process

For this process, we present an overview of the applications of ML in relation with the management and maintenance of production systems.

4.3.1. *Production management.* ML methods have been used since the early 2000s to solve three types of problems in production systems.

- To deal with the complexity of lot-sizing and scheduling decisions within production systems.
- As alternative to simulation modelling of production systems under uncertainty.
- For prediction purposes in production systems, such as yield and flow times prediction.

In the production literature dealing with ML techniques, there is a reference to two types of lot sizing problems: online and offline lot-sizing problems. The former refers to problems where only few future periods from the horizon are known whereas the latter refers to problems where the entire horizon is known. Both aim to optimize the size of the production batches where the data of the master production schedule are processes using ML taking into account uncertainties and other capacity and cost constraints. The literature dealing with the online lot-sizing problem started in the early 2000s where several ANNs are considered. For instance, the multi-layers perceptron (MLP) model combined with the KNN technique is used by Aarts *et al.* (2000). An ANN architecture that employs the back propagation

TABLE 3. Procurement applications of ML

SC application	ML method	Reference
Managing relationships	LR, NN	Pal <i>et al.</i> (2017)
Material usage reduction	DT, ANN	Kuo <i>et al.</i> (2021)
Partner selection	DT, RF	Wilson <i>et al.</i> (2020)
	RL	Kim <i>et al.</i> (2008)
	DT	Nepal & Yadav (2015)
	Polynomial regression, SVM	Islam <i>et al.</i> (2021)
	ANN	Wu & Barnes (2014)
Green supplier selection	ANN (backpropagation)	Lau <i>et al.</i> (2005)
3PL partner selection	ANN	Kuo <i>et al.</i> (2010)
Managing many partners in order to achieve best price per unit	ANN	Raut <i>et al.</i> (2017)
Information sharing management	NLP, RNN, K-means	Abdollahnejadbarough <i>et al.</i> (2020)
Supply chain relationship quality conditions	RF, SVM and LR	Sasaki & Sakata (2021)
Prediction of inefficiency and corruption in public procurement	ANN (backpropagation)	Tsai & Hung (2016)
	Gradient Boosting Machines (GBM), lasso classification	Gallego <i>et al.</i> (2021)
Pricing	RL	Deng (2023)

learning algorithm has also been used by [Chih-Ting Du & Wolfe \(2000\)](#) in conjunction with fuzzy logic controllers to refine inventory classification and hence help retrieve adequate lot-sizing decisions within a real-time MRP system.

Other applications of ANNs in lot sizing problems are proposed by [Rohde \(2004\)](#), [Mahdavi *et al.* \(2009\)](#) and [Van Hezewijk *et al.* \(2023\)](#). On the question of scheduling problems, open-shop scheduling problems are solved by [Colak & Agarwal \(2005\)](#) using augmented NN and by [Kim *et al.* \(2020\)](#) using more sophisticated DL techniques. A scheduling method using a real time selection of dispatching rules (through a DT) in combination with statistical process control charts (SPCC) is proposed by [Metan *et al.* \(2010\)](#). The proposed ML methods have been shown to outperform standard scheduling heuristics from the literature.

With regard to simulation of production systems, kanban based simulation models and meta-modelling of discrete event simulation of production lines subject to uncertainties have been analyzed by [Guner *et al.* \(2009\)](#), [Can & Heavey \(2012\)](#) and [Mohammad Nezhad & Mahlooji \(2014\)](#) using ANNs. This literature shows the cost benefit of ML-based models compared to the conventional simulation-optimization methods. ANNs have been shown especially to be associated with a reduced computational requirement compared to standard methods. Hence, it is clear from the literature that ML allows to create approximate models which sacrifices accuracy for a computational gain, knowing that simulation may have execution times that are computationally expensive. Moreover, the ML-based approach can develop models without underlying assumptions or a prior knowledge about the relationship between the control factors and the performance ([Can & Heavey, 2012](#)).

ML has also been used in the literature for prediction purposes in production systems. For example, the completion time and the tardiness of a job in the production process is estimated by [Ahmarofi et al. \(2017\)](#) using ANNs with feedforward MLP. Yields in different units of a multi-stage production/inventory system are predicted by [Cheng & Tang \(2018\)](#) using an SVR model. The consumption of spare parts in a communication network is predicted by [Mouronte-López \(2018\)](#) using an MLP NN model. More recently, ANNs have also been used by [Schneckenreither et al. \(2021\)](#) to forecast flow times in a manufacturing system for a dynamic setting of lead times that enables to determine order releases.

Hence, it is clear that a plethora of ML models have been considered to deal with production problems. ANNs and DL architectures are found to perform well given their proved effectiveness in optimizing batch-sizes and scheduling decisions within production systems with uncertainty. When dealing with simulation modelling, ANNs are also recommended given their flexibility and better computational efficiency compared to traditional simulation-optimization models. For prediction purposes, ANNs and SVR are suitable for accurately forecasting job completion times, yields and spare part consumption.

Finally, through this review, we have noticed that production has attracted several studied related to supply chain sustainability. In fact, the reduction of energy and materials, as well as their reuse through recycling/remanufacturing, has occupied researchers since 2020. Using primarily supervised but also unsupervised learning, they achieved the desired goals ([Behnamfar et al., 2022](#); [El Hathat et al., 2023](#); [Orošnjak et al., 2023](#); [Ali et al., 2023a](#)).

4.3.2. Maintenance. Studies focusing on optimizing maintenance tasks are particularly tightened around four main strategies, namely: predictive maintenance, preventive maintenance, condition-based maintenance (CBM) and total productive maintenance (TPM). The literature review reveals that predictive maintenance and CBM studies primarily refer to the DL approach, whereas preventive maintenance and TPM are more commonly explored using ML models. Predictive maintenance focuses on anticipating equipment failure rates, spare parts needs and maintenance costs ([Scarf et al., 2024](#)). Available studies emphasize the effectiveness of neural networks, most notably architectures that are adapted to sequential data such as LSTM and ANN models. Indeed, ANNs trained with sensor data can effectively predict equipment failure rates ([Fordal et al., 2023](#)), and LSTM networks outperform traditional statistical methods, such as ARIMA and SES ([Bampoula et al., 2021](#)).

CBM aims to minimize downtime by making maintenance decisions based on the observed condition of the equipment. Here, we shall point out that various approaches using ML models (e.g. RF, DT), RL, simple DL (e.g. ANN) and hybrid DL models (e.g., CNN-LSTM) have shown superior accuracy in predicting the remaining useful life (RUL) of equipment and optimizing maintenance schedules ([Accorsi et al., 2017](#); [Zhao et al., 2018](#); [Shcherbakov & Sai, 2022](#); [Yang et al., 2022](#)). On the other hand, preventive maintenance involves replacing or maintaining equipment components before their expected failure. Studies dealing with this maintenance strategy propose various ML frameworks using models such as RF, LR, KNN and SVM, which are often combined with feature extraction techniques, to accurately predict the RUL of equipments ([Bampoula et al., 2021](#); [Choudhury, 2021](#); [Gayialis et al., 2022](#)). In the context of TPM, ML applications focus on predicting machine failure times and optimizing maintenance processes. These studies aim to significantly increase the mean time between failures (MTBF) and enhance overall equipment reliability. Advanced ML models have shown promising results in improving maintenance efficiency and reliability metrics ([Mohan et al. \(2021\)](#), [Zhong et al. \(2017\)](#)).

[Table 4](#) provides a selection of studies that dealt with maintenance management using ML approaches.

It could be concluded that for effective maintenance strategies, one should refer to DL approaches such as LSTM for predictive maintenance in order to anticipate equipment failures and costs. Models

TABLE 4. Summary of ML applications in maintenance

SC application	ML method	References
Predictive maintenance		
Equipment failure rate prediction	ANN, LSTM	Fordal <i>et al.</i> (2023), Bampoula <i>et al.</i> (2021)
Predicting maintenance requirements for desired OEE	SVM, XGBoost, DL, RF	Hassani <i>et al.</i> (2019)
Preventive maintenance		
Predicting process routes for steel materials	RF, LR, KNN, SVM	Choudhury (2021)
Predicting useful life of equipment	LSTM-based DNN	Bampoula <i>et al.</i> (2021)
CBM		
Predicting RUL of systems	RF, DT, ANN	Accorsi <i>et al.</i> (2017)
Integrated CBM methodology for redundant systems	RL	Yang <i>et al.</i> (2022)
Complex multi-object systems failure risk prediction	CNN-LSTM hybrid	Shcherbakov & Sai (2022)
TPM		
Predicting time to failure of machines	Adaptive ARIMA	Mohan <i>et al.</i> (2021)
Intelligent techniques for TPM	IoT, cloud manufacturing	Zhong <i>et al.</i> (2017)

such as RF, DT, RL and hybrid CNN-LSTM are likely to be appropriate for tackling CBM issues to help to minimize downtime by predicting equipment's RUL. On the other hand, we advocate implementing ML frameworks that involve RF, LR, KNN and SVM for preventive maintenance to proactively predict equipment component failures.

4.4. DELIVER process

4.4.1. *Distribution.* Product distribution faces a constantly changing world. The increase in global population (Flores & Villalobos, 2020), urbanization (Tian *et al.*, 2021) and their consequences, such as hunger in many regions of the planet (Nair *et al.*, 2017), have made decision-making for goods distribution a challenging task. Researchers have attempted to address this challenge using advanced ML methods, particularly supervised learning.

Two additional issues in this field are the stochastic nature of goods' demand and the new online purchasing methods. In the former, unsupervised learning and RL have been applied, with researchers trying to manage distribution problems to various customers from a single origin (Achamrah *et al.*, 2022) and the variability among countries in this area (Federico *et al.*, 2023). RL succeeds in controlling the combinatorial complexity of each problem, which makes its use essential for many issues. Our research has identified supervised learning as the primary method for managing online purchases and thus their distribution. Using this method, authors-researchers have achieved timely and cost-effective delivery of products to customers (Salari *et al.*, 2022; Tao *et al.*, 2023).

The problem of locating business facilities, factories and warehouses, both central and otherwise, plays a vital role in goods distribution, whether for online orders or backorders. In this case, all three ML methods (supervised, unsupervised, RL) have been employed, with supervised learning being

predominant. Finding the appropriate location may involve selecting the right country (Canbolat *et al.*, 2007; Khalid & Herbert-Hansen, 2018) or, on a smaller scale, the right location within a city (Hsieh & Tien, 2004; Chang *et al.*, 2021; Kemmar *et al.*, 2021).

Extensive research has also been conducted on last-mile distribution. Supervised learning is once again applied here. It is used to calculate orders that will not be fulfilled in the near future using methods such as AdaBoost Regressor, Bayesian Ridge, and Decision Tree Regressor (Pegado-Bardayo *et al.*, 2023) and for faster order picking using the CNN method (Azizpour *et al.*, 2022). RL has also been applied to find the optimal continuously changing location of Mobile Parcel Lockers (Liu *et al.*, 2023) and to improve overall last-mile distribution (Dieter *et al.*, 2023).

It should be stated that there is a significant need to assist the newsvendor seller in a global market that is constantly changing, where all data are characterized by uncertainty. For this purpose, research using supervised learning has been conducted because sudden changes in demand cannot be managed with traditional methods (O'Neil *et al.*, 2016; Thoummala *et al.*, 2023).

Finally, this review recommends leveraging supervised learning to ensure timely and cost-effective deliveries, whereas unsupervised learning and RL might be used to handle the stochastic nature of demand and complex distribution challenges. For locating business facilities, apply a combination of supervised, unsupervised and RL methods. More specifically, supervised learning is likely to be the most prevalent. When dealing with last-mile distribution and the newsvendor problems, supervised learning should be employed for order calculations and faster order picking, while using RL enables for optimal mobile parcel locker locations and enhances overall distribution efficiency.

4.4.2. *Transportation.* Transportation involves more agents acting within SCs, especially in multi-echelon SC architectures, where Internet of Things (IoT) represents the data source converting supply chains into hyper-connected multi-layer networks (Ben-Daya *et al.*, 2019). By leveraging ML in supply chain transportation processes, companies can take more informed decisions, improve efficiency, reduce costs and enhance customer satisfaction. We can underline three main interrelated goals to reach in transportation by means of ML algorithms, in particular:

- Forecasting of travel time, traffic flow and transportation price.
- Real-time optimization of routing and schedules.
- Improve sustainability of transports.

The first goal responds to the need of making transports controllable by using historical and real-time data on transports. In particular, real-time data are often provided by IoT devices and enhance supply chain visibility through tracking and monitoring. Forecasting of travel time (e.g., Li *et al.* (2019) and Chen *et al.* (2021)), traffic flow (e.g., Moscoso-López *et al.* (2019)) and transportation price (e.g., Budak *et al.* (2017)), as well as the analysis of their explanatory variables (e.g., Merchan *et al.* (2020) and Chandra *et al.* (2022)), are generally dealt with supervised ML approaches, among which ANNs and decision trees are the most adopted ones.

In order to optimize real-time routing and schedules, i.e., the second goal that ML can pursue, historical and real-time data can be used again, but in this case to address changes in weather, traffic congestion and so on. RL reveals to be of a great potential in such dynamic environments, where it is used proactively and not only descriptively and predictively. Indeed, RL is extensively applied in optimization problems such as trailer loading (Jung & Yang, 2023) and minimizing transportation costs (Xiang *et al.*, 2023). As already underlined, RL effectively addresses problems characterized by dynamic conditions (Basso *et al.*, 2022; Van Steenbergen *et al.*, 2023; Zhao & Liang, 2023), offering

new solutions to long-standing issues. Port and terminal logistics represents an interesting application field both of RL (e.g., [Irannezhad et al. \(2020\)](#)) and of ANN (e.g., [Becker et al. \(2016\)](#)) for routing decisions, due to the complexity of managing more interacting agents that face dynamic changes, with the aim of decreasing costs and achieving higher utilization of trucks. Besides ports and terminal logistics, routing decisions are even more crucial for reducing food waste and ensuring product safety in the fresh food transportation. Thereby, it is not surprising that ML is extensively applied in this sector as well, for example for maintaining low-temperature environments. For the application of ML to fresh food transportation, the reader is referred to [Konovalenko et al. \(2021\)](#) and [Lim et al. \(2022\)](#).

Finally, the third goal refers to the improvement of the environmental sustainability of transports, which can be reached by means of supervised and unsupervised ML approaches (e.g., [Hao et al. \(2018\)](#), [El Khalili et al. \(2022\)](#), [Mohanty et al. \(2018\)](#) and [Arunmozhi et al. \(2022\)](#)), but there is a notable extensive use of RL, especially for location problems (e.g., [Leng et al. \(2023\)](#), [Zou et al. \(2022\)](#)). In summary, since transports take place in increasingly dynamic and complex environments, real-time data and RL approaches are proving to be of great support, especially in solving routing problems while adapting to dynamic conditions such as weather and traffic. In particular, the sectors that have been the most extensively investigated due to their complexity in management are port logistics and fresh food transportation.

[Table 5](#) summarizes the main areas of application of ML in the transportation literature.

4.5. RETURN process

Research on ML applied to sustainable supply chains with return flows has been ongoing since 2018. A longstanding issue, recycling, was addressed by [Hao et al. \(2018\)](#) paving the way for other researchers to incorporate it into all areas of logistics. The uncertainty and non-linearity of the problem compelled researchers to apply advanced optimization techniques to using ANN. Recycling, naturally, remains a focal point for researchers today as it offers a holistic view of the supply chain ([Ashtab & Tosarkani, 2023](#)), where LR also finds application.

Predicting product returns is crucial for the smooth operation of a business or industry, as returns can sometimes reach up to 30% of products. In the related literature, the study by [Cui et al. \(2020\)](#) consists an attempt to apply this whereby RF and Gradient Boosting techniques are referred to. It has also been performed to deal with the complexity in an industry where there is a rapid withdrawal of goods, specifically the clothing retail sector, by [Tüylü & Eroğlu \(2019\)](#) using DT, ANNs and SVR.

5. Conclusions

The applications of ML in SCM are continuously evolving, offering immense potential for enhancing efficiency and competitiveness. We have conducted an SLR to identify the papers dealing with SCM issues and using ML techniques. A total of 415 papers have been deeply reviewed and our statistical analysis of these papers has shown a considerable expansion of the number of publications from 2019. The analysis has revealed that supervised learning is the most used category of ML techniques within the literature with a clear increase in the applications of the RL methods since 2019. We have identified eight research areas in SCM, that we have classified into five processes as defined by the SCOR model, where ML has been applied. Moreover, we have shown that demand forecasting is the area that has attracted most of the ML applications followed by inventory management and transportation. Note that RL is particularly well used in these two latter areas, which is explained by the fact that they involve typical short-term decisions that require frequent and fast decision-making, which can be obtained with RL algorithms.

TABLE 5. *ML applications in transportation*

SC application	ML method	Reference
Forecasting travel time	DT (gradient boosting partitioned regression tree (GBPRT))	Chen <i>et al.</i> (2021)
	RF, Gradient Boosting Regression Tree (GBRT)	Li <i>et al.</i> (2019)
Forecasting traffic flow	DT (GBPRT)	Moscoso-López <i>et al.</i> (2019)
Forecasting transportation price	DT (GBPRT)	Budak <i>et al.</i> (2017)
Explanatory variables of traffic	RF	Merchan <i>et al.</i> (2020)
	RF, GBRT	Chandra <i>et al.</i> (2022)
Trailer loading	cerca	Jung & Yang (2023)
Minimizing transportation costs	cerca	Xiang <i>et al.</i> (2023)
Routing decision	RL	Zhao & Liang (2023), Van Steenberg <i>et al.</i> (2023), Irannezhad <i>et al.</i> (2020), Basso <i>et al.</i> (2022)
	ANN	Becker <i>et al.</i> (2016)
Forecasting and control of temperature in cold supply chains	ANN	Konovalenko <i>et al.</i> (2021)
	ELM	Lim <i>et al.</i> (2022)
Forecasting the number of end-of-life vehicles	ANN	Hao <i>et al.</i> (2018)
Air quality improvement	ANN	El Khalili <i>et al.</i> (2022)
Carbon emissions reduction	Kohonen self-organizing map (KSOM)	Mohanty <i>et al.</i> (2018)
Sustainability of autonomous vehicle SC	SVM, K-means	Arunmozhi <i>et al.</i> (2022)
Low-carbon SC design	RL	Leng <i>et al.</i> (2023), Zou <i>et al.</i> (2022)

We have noticed that exploring ML tools has become a common practice in recent research studies, given their ability to accurately handle supply chain research questions that typically involve large-scale problems and complex data such as in production (multi-stage systems) and procurement (multiple suppliers) or the high size of the decision problem such as in inventory management (multiple states due to the stochasticity and dynamic nature). Note also that the positive trend in the use of ML in SCM is naturally explained by the recent progress in algorithmic, computational capability of computers and data technologies.

While the application of ML in the SCM research has shown significant promise and yielded numerous benefits, several research gaps are yet to be addressed. These gaps present opportunities for future investigation and innovation in this dynamic field. The first gap relates to the use of RL in the literature. Indeed, RL has been mostly used in the inventory control and transportation literature and its use is constantly increasing over the years. Within this ML category, the Q-learning algorithm is the most popular algorithm. However, more work should be done in other applications, especially in demand forecasting, to benefit from its learning power, which can lead to a high performance. Moreover, it is

worth noting that the high performance of RL in the literature has been shown through relatively simple SC cases due to the lack of available data of real systems where even more complex structures and huge size exist. Making the data of such contexts available by managers would lead to higher performance and offer a substantial opportunity of big value for companies.

With regard to transportation, although we have cited papers that cover ML and the use of all the means of transport separately, there is a gap in the studies that regard combinations of means of transport. Bridging this gap would be fruitful for transportation researchers and practitioners because multimodal transport is nowadays ubiquitous in many transportation companies due to their business expansion. In fact, under such context, ML can be used not only as a predictive tool that includes several factors impacting the multimodal transportation, but also as an optimization tool that deals with the complexity in finding near optimal solutions when different modes are considered.

The literature that deals with maintenance management is found to rely on well-established ML approaches such as RF, DT and ANN. While these methods can be effective, we find it judicious to investigate the scope yield by alternative peer models. Indeed, maintenance challenges may vary widely due to the variable complexity of equipments and operational constraints. As such, adapted ML models to effectively address specific challenges reveals appropriate. In this vein, sophisticated deep NNs, and most notably, recurrent and convolutional NNs represent effective candidate models to analyze complex time-series data that are retrieved from sensors and equipments. Moreover, we have noticed that the literature dealing with CBM and TPM exploring ML techniques is restricted compared to other maintenance tasks addressed by ML in SCM. In addition, the ML literature mainly rely on traditional ML techniques and, therefore, more specific and advanced architectures need to be developed to enhance the performance of the models and make them more applicable in real-world scenarios.

It is worth pointing out that despite the huge literature dealing with closed loop supply chains and returns, where several methods have been used to simulate or optimize the performance of the considered systems, very few have used ML. This gap in the literature constitutes an important avenue for further research, especially that ML can deal with the complexity induced by the co-existence of both forward and return flows in supply chains.

Note also that given the continuous progress in ML architectures, a rapid proliferation of models is encountered. Here, it should be pointed out that this proliferation yields a challenge by obscuring the most suitable ML approaches for specific SCM application. Thereby, there exists a crucial need to develop a comprehensive interpretive tool that would illustrate the most appropriate ML methods based on the specific features and their associated value ranges within a given SCM scenario. This tool would empower decision-makers and researchers to identify the most favourable ML approaches and hence, allows more effective data-driven strategies in the realm of SCM.

Finally, AI has seen a considerable advancement over the last years and it has become much broader than the common ML techniques discussed in this paper. New tools, including GAI techniques such as generative adversarial networks (GANs) and transformers along with applications like Chat-GPT, GitHub Copilot, DALL-E, etc. have been developed. These tools are particularly useful for generating scenarios in cases of insufficient data or for generating possible future scenarios, which are common problems for example in demand forecasting. An interesting avenue for further research would be to analyze the application of these advanced AI tools in the SCM literature.

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Data availability

No data were generated or used as part of this research.

REFERENCES

- AARTS, E. H., REIJNHOUT, M., STEHOUEW, H. & WESSELS, J. (2000) A novel decomposition approach for on-line lot-sizing. *Eur. J. Oper. Res.*, **122**, 339–353.
- ABDOLLAHNEJADBAROUGH, H., MUPPARAJU, K. S., SHAH, S., GOLDING, C. P., LEITES, A. C., POPP, T. D., SHROYER, E., GOLANY, Y. S., ROBINSON, A. G. & AKGUN, V. (2020) Verizon uses advanced analytics to rationalize its tail spend suppliers. *INFORMS J. Appl. Anal.*, **50**, 197–211.
- ABDULLA, A., BARYANNIS, G. & BADI, I. (2023) An integrated machine learning and marcos method for supplier evaluation and selection. *Decis. Anal. J.*, **9**, 100342.
- ACCORSI, R., MANZINI, R., PASCARELLA, P., PATELLA, M. & SASSI, S. (2017) Data mining and machine learning for condition-based maintenance. *Procedia Manuf.*, **11**, 1153–1161.
- ACHAMRAH, F. E., RIANE, F. & LIMBOURG, S. (2022) Solving inventory routing with transshipment and substitution under dynamic and stochastic demands using genetic algorithm and deep reinforcement learning. *Int. J. Prod. Res.*, **60**, 6187–6204.
- AHMAROFI, A. A., RAMLI, R. & ZAINAL ABIDIN, N. (2017) Predicting completion time for production line in a supply chain system through artificial neural networks. *Int. J. Supply Chain Manag.*, **6**, 82–90.
- AKBABA, M. M. & ÇETIN, O. (2022) Supplier performance evaluation using cluster analysis and artificial neural networks in a MRO business in aviation sector. *Corporate Governance, Sustainability, and Information Systems in the Aviation Sector*, vol. **I**. Springer, pp. 177–192.
- AKBARI, M. & DO, T. N. A. (2021) A systematic review of machine learning in logistics and supply chain management: current trends and future directions. *Benchmarking: Int. J.*, **28**, 2977–3005.
- AKIN ATEŞ, M., SUURMOND, R., LUZZINI, D. & KRAUSE, D. (2022) Order from chaos: a meta-analysis of supply chain complexity and firm performance. *J. Supply Chain Manag.*, **58**, 3–30.
- ALI, S. S., KAUR, R., PERSIS, D. J., SAHA, R., PATTUSAMY, M. & SREEDHARAN, V. R. (2023a) Developing a hybrid evaluation approach for the low carbon performance on sustainable manufacturing environment. *Ann. Oper. Res.*, **324**, 249–281.
- ALI, M. R., NIPU, S. M. A. & KHAN, S. A. (2023b) A decision support system for classifying supplier selection criteria using machine learning and random forest approach. *Decis. Anal. J.*, **7**, 100238.
- ARUNMOZHI, M., VENKATESH, V., ARISIAN, S., SHI, Y. & SREEDHARAN, V. R. (2022) Application of blockchain and smart contracts in autonomous vehicle supply chains: an experimental design. *Transp. Res. E Logist. Transp. Rev.*, **165**, 102864.
- ASADI, A. & PINKLEY, S. N. (2021) A stochastic scheduling, allocation, and inventory replenishment problem for battery swap stations. *Transp. Res. E Logist. Transp. Rev.*, **146**, 102212.
- ASHTAB, S. & TOSARKANI, B. M. (2023) Scenario-based multi-objective optimisation model based on supervised machine learning to configure a plastic closed-loop supply chain network. *Int. J. Bus. Perform. Supply Chain Model.*, **14**, 106–128.
- AZIZPOUR, M., NAMAZYPOUR, N. & KIRCHHEIM, A. (2022) Synthetic data generation for robotic order picking. *Logist. J.: Proc.*, **2022**.
- BABAI, M., TSADIRAS, A. & PAPADOPOULOS, C. (2020) On the empirical performance of some new neural network methods for forecasting intermittent demand. *IMA J. Manag. Math.*, **31**, 281–305.
- BAMPOULA, X., SIATERLIS, G., NIKOLAKIS, N. & ALEXOPOULOS, K. (2021) A deep learning model for predictive maintenance in cyber-physical production systems using LSTM autoencoders. *Sensors*, **21**, 972.
- BAN, G.-Y. & RUDIN, C. (2019) The big data newsvendor: practical insights from machine learning. *Oper. Res.*, **67**, 90–108.
- BARROS, O., WEBER, R. & REVECO, C. (2021) Demand analysis and capacity management for hospital emergencies using advanced forecasting models and stochastic simulation. *Oper. Res. Perspect.*, **8**, 100208.

- BASSO, R., KULCSÁR, B., SANCHEZ-DIAZ, I. & QU, X. (2022) Dynamic stochastic electric vehicle routing with safe reinforcement learning. *Transp. Res. E Logist. Transp. Rev.*, **157**, 102496.
- BECKER, T., ILLIGEN, C., MCKELVEY, B., HÜLSMANN, M. & WINDT, K. (2016) Using an agent-based neural-network computational model to improve product routing in a logistics facility. *Int. J. Prod. Econ.*, **174**, 156–167.
- BEHNAMFAR, R., SAJADI, S. M. & TOOTOONCHY, M. (2022) Developing environmental hedging point policy with variable demand: a machine learning approach. *Int. J. Prod. Econ.*, **254**, 108640.
- BEN-DAYA, M., HASSINI, E. & BAHROUN, Z. (2019) Internet of things and supply chain management: a literature review. *Int. Journal of Prod. Res.*, **57**, 4719–4742.
- BERTSIMAS, D. & KALLUS, N. (2020) From predictive to prescriptive analytics. *Manag. Sci.*, **66**, 1025–1044.
- BERTSIMAS, D., MCCORD, C. & STURT, B. (2023) Dynamic optimization with side information. *Eur. J. Oper. Res.*, **304**, 634–651.
- BODENDORF, F., MERKL, P. & FRANKE, J. (2022) Artificial neural networks for intelligent cost estimation—a contribution to strategic cost management in the manufacturing supply chain. *Int. J. Prod. Res.*, **60**, 6637–6658.
- BOONE, T., GANESHAN, R., JAIN, A. & SANDERS, N. R. (2019) Forecasting sales in the supply chain: consumer analytics in the big data era. *Int. J. Forecast.*, **35**, 170–180.
- BOUTE, R. N., GJISBRECHTS, J., VAN JAARVELD, W. & VANVUCHELEN, N. (2022) Deep reinforcement learning for inventory control: a roadmap. *Eur. J. Oper. Res.*, **298**, 401–412.
- BROOKES, T., NIKOLOPOULOS, K., LITSIOU, K. & ALGHASSAB, W. (2024) Forecasting and planning for special events in the pulp and paper supply chains. *Supply Chain Forum: Int. J.*, 1–18. Available at: <https://doi.org/10.1080/16258312.2024.2315029>.
- BUDAK, A., USTUNDAG, A. & GULOGLU, B. (2017) A forecasting approach for truckload spot market pricing. *Transp. Res. A: Policy Pract.*, **97**, 55–68.
- CAN, B. & HEAVEY, C. (2012) A comparison of genetic programming and artificial neural networks in metamodeling of discrete-event simulation models. *Comput. Oper. Res.*, **39**, 424–436.
- CANBOLAT, Y. B., CHELST, K. & GARG, N. (2007) Combining decision tree and MAUT for selecting a country for a global manufacturing facility. *Omega*, **35**, 312–325.
- CAO, Y. & SHEN, Z.-J. M. (2019) Quantile forecasting and data-driven inventory management under nonstationary demand. *Oper. Res. Lett.*, **47**, 465–472.
- CARBONNEAU, R., LAFRAMBOISE, K. & VAHIDOV, R. (2008) Application of machine learning techniques for supply chain demand forecasting. *Eur. J. Oper. Res.*, **184**, 1140–1154.
- CHAHARSOOGHI, S. K., HEYDARI, J. & ZEGORDI, S. H. (2008) A reinforcement learning model for supply chain ordering management: an application to the beer game. *Decis. Support Syst.*, **45**, 949–959.
- CHANDRA, A., PANI, A., SAHU, P. K., MAJUMDAR, B. B. & SHARMA, S. (2022) Identifying large freight traffic generators and investigating the impacts on travel pattern: a decision tree approach for last-mile delivery management. *Res. Transp. Bus. Manag.*, **43**, 100695.
- CHANG, X., WU, J., SUN, H., DE ALMEIDA CORREIA, G. H. & CHEN, J. (2021) Relocating operational and damaged bikes in free-floating systems: a data-driven modeling framework for level of service enhancement. *Transp. Res. A: Policy Pract.*, **153**, 235–260.
- CHATHA, K. A. & JALIL, M. (2022) Complexity in three-echelon supply chain network and manufacturing firm's operational performance. *Comput. Ind. Eng.*, **169**, 108196.
- CHEN, S. & CHEN, Y. (2023) Designing a resilient supply chain network under ambiguous information and disruption risk. *Comput. Chem. Eng.*, **179**, 108428.
- CHEN, Y.-T., SUN, E. W., CHANG, M.-F. & LIN, Y.-B. (2021) Pragmatic real-time logistics management with traffic IoT infrastructure: big data predictive analytics of freight travel time for Logistics 4.0. *Int. J. Prod. Econ.*, **238**, 108157.
- CHEN, B., SIMCHI-LEVI, D., WANG, Y. & ZHOU, Y. (2022) Dynamic pricing and inventory control with fixed ordering cost and incomplete demand information. *Manag. Sci.*, **68**, 5684–5703.
- CHENG, C. & TANG, L. (2018) Robust policies for a multi-stage production/inventory problem with switching costs and uncertain demand. *Int. J. Prod. Res.*, **56**, 4264–4282.

- CHIH-TING DU, T. & WOLFE, P. M. (2000) Building an active material requirements planning system. *Int. J. Prod. Res.*, **38**, 241–252.
- CHOUDHURY, A. (2021) Processing technique selection for steels based on mechanical properties using machine learning framework. *Research Square*. Available at: <https://orcid.org/0000-0001-5153-4449>.
- CLAUSEN, J. B. B. & LI, H. (2022) Big data driven order-up-to level model: application of machine learning. *Comput. Oper. Res.*, **139**, 105641.
- COLAK, S. & AGARWAL, A. (2005) Non-greedy heuristics and augmented neural networks for the open-shop scheduling problem. *Nav. Res. Logist. (NRL)*, **52**, 631–644.
- CROSTON, J. D. (1972) Forecasting and stock control for intermittent demands. *J. Oper. Res. Soc.*, **23**, 289–303.
- CUI, H., RAJAGOPALAN, S. & WARD, A. R. (2020) Predicting product return volume using machine learning methods. *Eur. J. Oper. Res.*, **281**, 612–627.
- DE MOOR, B. J., GIJSBRECHTS, J. & BOUTE, R. N. (2022) Reward shaping to improve the performance of deep reinforcement learning in perishable inventory management. *Eur. J. Oper. Res.*, **301**, 535–545.
- DEBNATH, R., MAJUMDER, P., TARAFDAR, A., BHATTACHARYA, B. & BERA, U. K. (2024) Artificial intelligence based supply chain management strategy during COVID-19 situation. *Supply Chain Forum: Int. J.*, in press. Available at: <https://doi.org/10.1080/16258312.2024.2303307>.
- DENG, G. (2023) Dynamic price competition market for retailers in the context of consumer learning behavior and supplier competition: machine learning-enhanced agent-based modeling and simulation. *Adv. Prod. Eng. Manag.*, **18**, 434–446.
- DENIZ, N. & ÖZCEYLAN, E. (2023) A bibliometric and social network analysis of data-driven heuristic methods for logistics problems. *J. Ind. Manag. Optim.*, **19**, 5671–5689.
- DIETER, P., CARON, M. & SCHRYEN, G. (2023) Integrating driver behavior into last-mile delivery routing: combining machine learning and optimization in a hybrid decision support framework. *Eur. J. Oper. Res.*, **311**, 283–300.
- EL HATHAT, Z., SREEDHARAN, V. R., VENKATESH, V., ZOUADI, T., ARUNMOZHI, M. & SHI, Y. (2023) Modelling and analyzing the GHG emissions in the VUCA world: evidence from tomato production in Morocco. *J. Clean. Prod.*, **382**, 134862.
- EL KHALILI, M., TERRADA, L., OUAJJI, H. & DAAIF, A. (2022) Towards a green supply chain based on smart urban traffic using deep learning approach. *Stat. Optim. Inf. Comput.*, **10**, 25–44.
- FACCIO, M. (2015) Service spare parts versus production parts: a centralised or decentralised warehouse? *Int. J. Logist. Syst. Manag.*, **20**, 516–535.
- FEDERICO, L., MOUNIM, A., D'URSO, P. & DE GIOVANNI, L. (2023) Complex networks and deep learning for copper flow across countries. *Ann. Oper. Res.*, **339**, 937–963.
- FEIZABADI, J. (2022) Machine learning demand forecasting and supply chain performance. *Int. J. Logist. Res. Appl.*, **25**, 119–142.
- FERREIRA, K. J., LEE, B. H. A. & SIMCHI-LEVI, D. (2016) Analytics for an online retailer: demand forecasting and price optimization. *Manuf. Serv. Oper. Manag.*, **18**, 69–88.
- FLORES, H. & VILLALOBOS, J. R. (2020) A stochastic planning framework for the discovery of complementary, agricultural systems. *Eur. J. Oper. Res.*, **280**, 707–729.
- FORDAL, J. M., SCHJØLBERG, P., HELGETUN, H., SKJERMO, T. Ø., WANG, Y. & WANG, C. (2023) Application of sensor data based predictive maintenance and artificial neural networks to enable Industry 4.0. *Adv. Manuf.*, **11**, 248–263.
- FU, Y. & FISHER, M. (2023) The value of social media data in fashion forecasting. *Manuf. Serv. Oper. Manag.*, **25**, 1136–1154.
- GALLEGO, J., RIVERO, G. & MARTÍNEZ, J. (2021) Preventing rather than punishing: an early warning model of malfeasance in public procurement. *Int. J. Forecast.*, **37**, 360–377.
- GALLI, L., LEVATO, T., SCHOEN, F. & TIGLI, L. (2021) Prescriptive analytics for inventory management in health care. *J. Oper. Res. Soc.*, **72**, 2211–2224.
- GAUTAM, N., NAYAK, S. & SHEBALOV, S. (2023) Machine learning approach to market behavior estimation with applications in revenue management. In: Vinod, B. (eds) *Artificial Intelligence and Machine Learning in the Travel Industry*. Palgrave Macmillan, Cham. https://doi.org/10.1007/978-3-031-25456-7_11.

- GAYIALIS, S. P., KECHAGIAS, E. P., KONSTANTAKOPOULOS, G. D. & PAPADOPOULOS, G. A. (2022) A predictive maintenance system for reverse supply chain operations. *Logistics*, **6**, 4.
- GEORGIEV, S., POLYCHRONAKIS, Y., SAPOUNTZIS, S. & POLYCHRONAKIS, N. (2024) The role of artificial intelligence in project management: a supply chain perspective. *Supply Chain Forum: Int. J.*, in press. Available at: <https://doi.org/10.1080/16258312.2024.2384823>.
- GIANNOCCARO, I. & PONTRANOLFO, P. (2002) Inventory management in supply chains: a reinforcement learning approach. *Int. J. Prod. Econ.*, **78**, 153–161.
- GUSBRECHTS, J., BOUTE, R. N., VAN MIEGHEM, J. A. & ZHANG, D. J. (2022) Can deep reinforcement learning improve inventory management? Performance on lost sales, dual-sourcing, and multi-echelon problems. *Manuf. Serv. Oper. Manag.*, **24**, 1349–1368.
- GIRI, C. & CHEN, Y. (2022) Deep learning for demand forecasting in the fashion and apparel retail industry. *Forecasting*, **4**, 565–581.
- GOEDHART, J., HAIJEMA, R. & AKKERMAN, R. (2023) Modelling the influence of returns for an omni-channel retailer. *Eur. J. Oper. Res.*, **306**, 1248–1263.
- GOPAL, P., RANA, N. P., KRISHNA, T. V. & RAMKUMAR, M. (2024) Impact of big data analytics on supply chain performance: an analysis of influencing factors. *Ann. Oper. Res.*, **333**, 769–797.
- GUNERI, A., KUZU, A. & TASKIN GUMUS, A. (2009) Flexible kanbans to enhance volume flexibility in a JIT environment: a simulation based comparison via ANNs. *Int. J. Prod. Res.*, **47**, 6807–6819.
- GUPTA, S., RIKHTEHGAR BERENJI, H., SHUKLA, M. & MURTHY, N. N. (2023) Opportunities in farming research from an operations management perspective. *Prod. Oper. Manag.*, **32**, 1577–1596.
- GUTIERREZ, R. S., SOLIS, A. O. & MUKHOPADHYAY, S. (2008) Lumpy demand forecasting using neural networks. *Int. J. Prod. Econ.*, **111**, 409–420.
- HAN, X. & CHEN, Q. (2021) Sustainable supply chain management: dual sales channel adoption, product portfolio and carbon emissions. *J. Clean. Prod.*, **281**, 125127.
- HAO, H., ZHANG, Q., WANG, Z. & ZHANG, J. (2018) Forecasting the number of end-of-life vehicles using a hybrid model based on grey model and artificial neural network. *J. Clean. Prod.*, **202**, 684–696.
- HASSAN, I. (2022) Machine learning techniques for supply chain management: a systematic literature review. *J. Syst. Manag. Sci.*, **12**, 79–136.
- HASSAN, L. A. H., MAHMASSANI, H. S. & CHEN, Y. (2020) Reinforcement learning framework for freight demand forecasting to support operational planning decisions. *Transp. Res. E Logist. Transp. Rev.*, **137**, 101926.
- HASSANI, I. E., MAZGUALDI, C. E. & MASROUR, T. (2019) Artificial intelligence and machine learning to predict and improve efficiency in manufacturing industry. arXiv preprint arXiv:1901.02256. Available at: <https://doi.org/10.48550/arXiv.1901.02256>.
- HSIEH, K.-H. & TIEN, F.-C. (2004) Self-organizing feature maps for solving location–allocation problems with rectilinear distances. *Comput. Oper. Res.*, **31**, 1017–1031.
- HUBER, J., MÜLLER, S., FLEISCHMANN, M. & STUCKENSCHMIDT, H. (2019) A data-driven newsvendor problem: from data to decision. *Eur. J. Oper. Res.*, **278**, 904–915.
- IRANNEZHAD, E., PRATO, C. G. & HICKMAN, M. (2020) An intelligent decision support system prototype for hinterland port logistics. *Decis. Support Syst.*, **130**, 113227.
- ISLAM, S., AMIN, S. H. & WARDLEY, L. J. (2021) Machine learning and optimization models for supplier selection and order allocation planning. *Int. J. Prod. Econ.*, **242**, 108315.
- JAHANI, H., JAIN, R. & IVANOV, D. (2023) Data science and big data analytics: a systematic review of methodologies used in the supply chain and logistics research. *Ann. Oper. Res.* Available at: <https://doi.org/10.1007/s10479-023-05390-7>.
- JALALI, H. & MENEZES, M. B. (2024) Product portfolio adjustments and the bullwhip effect: the impact of product introduction and retirement. *Eur. J. Oper. Res.*, **318**, 87–99.
- JIANG, P., HUANG, Y. & LIU, X. (2021) Intermittent demand forecasting for spare parts in the heavy-duty vehicle industry: a support vector machine model. *Int. J. Prod. Res.*, **59**, 7423–7440.
- JUNG, S. H. & YANG, Y. (2023) On the value of operational flexibility in the trailer shipment and assignment problem: data-driven approaches and reinforcement learning. *Int. J. Prod. Econ.*, **264**, 108979.

- KATSALIAKI, K., GALETSI, P. & KUMAR, S. (2022) Supply chain disruptions and resilience: a major review and future research agenda. *Ann. Oper. Res.*, **319**, 965–1002.
- KAYA, A., KAYA, G. & ÇEBELI, F. (2022) Forecasting automobile sales in Turkey with artificial neural networks. *Research Anthology on Artificial Neural Network Applications*. IGI Global, 1478–1489.
- KEMMAR, O., BOUAMRANE, K. & GELAREH, S. (2021) Hub location problem in round-trip service applications. *RAIRO-Oper. Res.*, **55**, S2831–S2858.
- KHALID, W. & HERBERT-HANSEN, Z. N. L. (2018) Using k-means clustering in international location decision. *J. Glob. Oper. Strateg. Sourc.*, **11**, 274–300.
- KIM, T., BILSEL, R. U. & KUMARA, S. (2008) Supplier selection in dynamic competitive environments. *Int. J. Serv. Oper. Inform.*, **3**, 283–293.
- KIM, B., JEONG, Y. & SHIN, J. G. (2020) Spatial arrangement using deep reinforcement learning to minimise rearrangement in ship block stockyards. *Int. J. Prod. Res.*, **58**, 5062–5076.
- KONOVALENKO, I., LUDWIG, A. & LEOPOLD, H. (2021) Real-time temperature prediction in a cold supply chain based on Newton's law of cooling. *Decis. Support Syst.*, **141**, 113451.
- KOULOURIOTIS, D. E. & MANTAS, G. (2012) Health products sales forecasting using computational intelligence and adaptive neuro fuzzy inference systems. *Oper. Res.*, **12**, 29–43.
- KOURENTZES, N. (2013) Intermittent demand forecasts with neural networks. *Int. J. Prod. Econ.*, **143**, 198–206.
- KUMARI, S., VENKATESH, V., TAN, F. T. C., BHARATHI, S. V., RAMASUBRAMANIAN, M. & SHI, Y. (2023) Application of machine learning and artificial intelligence on agriculture supply chain: a comprehensive review and future research directions. *Ann. Oper. Res.*, in press. Available at: <https://doi.org/10.1007/s10479-023-05556-3>.
- KUO, R. J., WANG, Y. C. & TIEN, F. C. (2010) Integration of artificial neural network and MADA methods for green supplier selection. *J. Clean. Prod.*, **18**, 1161–1170.
- KUO, T.-C., PENG, C.-Y. & KUO, C.-J. (2021) Smart support system of material procurement for waste reduction based on big data and predictive analytics. *Int. J. Logist. Res. Appl.*, **27**, 243–260.
- LAMBA, K. & SINGH, S. P. (2017) Big data in operations and supply chain management: current trends and future perspectives. *Prod. Plan. Control.*, **28**, 877–890.
- LAU, H. C., NING, A., PUN, K. F., CHIN, K.-S. & IP, W. (2005) A knowledge-based system to support procurement decision. *J. Knowl. Manag.*, **9**, 87–100.
- LENG, L., WANG, Z., WAN, A., ZHAO, Y., LIU, Y. & ZUO, Q. (2023) Joint impacts of ambient temperature, path flexibility, and hybrid fleet on energy-conserving supply chain network. *J. Clean. Prod.*, **423**, 138685.
- LEUNG, M. T., QUINTANA, R. & CHEN, A.-S. (2009) Make-to-order product demand forecasting: exponential smoothing models with neural network correction. *Advances in Business and Management Forecasting (Advances in Business and Management Forecasting, Vol. 6)*. Emerald Group Publishing Limited, Leeds, 249–266.
- LI, X., BAI, R., SIEBERS, P.-O. & WAGNER, C. (2019) Travel time prediction in transport and logistics: towards more efficient vehicle GPS data management using tree ensemble methods. *VINE J. Inf. Knowl. Manag. Syst.*, **49**, 277–306.
- LIM, M. K., LI, Y., WANG, C. & TSENG, M.-L. (2022) 'Prediction of cold chain logistics temperature using a novel hybrid model based on the mayfly algorithm and extreme learning machine. *Ind. Manag. Data Syst.*, **122**, 819–840.
- LIU, Y., YE, Q., ESCRIBANO-MACIAS, J., FENG, Y., CANDELA, E. & ANGELOUDIS, P. (2023) Route planning for last-mile deliveries using mobile parcel lockers: a hybrid q-learning network approach. *Transp. Res. E Logist. Transp. Rev.*, **177**, 103234.
- LOLLI, F., GAMBERINI, R., REGATTIERI, A., BALUGANI, E., GATOS, T. & GUCCI, S. (2017) Single-hidden layer neural networks for forecasting intermittent demand. *Int. J. Prod. Econ.*, **183**, 116–128.
- LOLLI, F., BALUGANI, E., ISHIZAKA, A., GAMBERINI, R., RIMINI, B. & REGATTIERI, A. (2019) Machine learning for multi-criteria inventory classification applied to intermittent demand. *Prod. Plan. Control.*, **30**, 76–89.
- LOUREIRO, A. L., MIGUÉIS, V. L. & DA SILVA, L. F. (2018) Exploring the use of deep neural networks for sales forecasting in fashion retail. *Decis. Support Syst.*, **114**, 81–93.
- MA, H.-L., SUN, Y., CHUNG, S.-H. & CHAN, H. K. (2022) Tackling uncertainties in aircraft maintenance routing: a review of emerging technologies. *Transp. Res. E Logist. Transp. Rev.*, **164**, 102805.

- MAHDAVI, I., SHIRAZI, B., SOLIMANPUR, M. & SAHEBJAMNIA, N. (2009) Lot size approximation based on minimising total delay in a shop with multi-assembly products. *Int. J. Prod. Res.*, **47**, 2685–2703.
- MAKRIDAKIS, S. & HIBON, M. (2000) The m3-competition: results, conclusions and implications. *Int. J. Forecast.*, **16**, 451–476.
- MAKRIDAKIS, S., ANDERSEN, A., CARBONE, R., FILDES, R., HIBON, M., LEWANDOWSKI, R., NEWTON, J., PARZEN, E. & WINKLER, R. (1982) The accuracy of extrapolation (time series) methods: results of a forecasting competition. *J. Forecast.*, **1**, 111–153.
- MAKRIDAKIS, S., CHATFIELD, C., HIBON, M., LAWRENCE, M., MILLS, T., ORD, K. & SIMMONS, L. F. (1993) The m2-competition: a real-time judgmentally based forecasting study. *Int. J. Forecast.*, **9**, 5–22.
- MAKRIDAKIS, S., SPILLOTIS, E. & ASSIMAKOPOULOS, V. (2020) The m4 competition: 100,000 time series and 61 forecasting methods. *Int. J. Forecast.*, **36**, 54–74.
- MAKRIDAKIS, S., SPILLOTIS, E. & ASSIMAKOPOULOS, V. (2022) M5 accuracy competition: results, findings, and conclusions. *Int. J. Forecast.*, **38**, 1346–1364.
- MAMOUDAN, M. M., MOHAMMADNAZARI, Z., OSTADI, A. & ESFAHBODI, A. (2022) Food products pricing theory with application of machine learning and game theory approach. *Int. J. Prod. Res.*, **62**, 5489–5509.
- MANOHAR, H. L. & KUMAR, R. G. (2020) A neural networks model for green supplier selection. *Int. J. Serv. Oper. Manag.*, **35**, 1–11.
- MENDONÇA, G. D. & JUNIOR, O. F. L. (2023) Artificial intelligence applied to supply chain operations management: a systematic literature review. *Int. J. Logist. Syst. Manag.*, **45**, 1–30.
- MERCHAN, D., WINKENBACH, M. & SNOECK, A. (2020) Quantifying the impact of urban road networks on the efficiency of local trips. *Transp. Res. A: Policy Pract.*, **135**, 38–62.
- METAN, G., SABUNCUOGLU, I. & PIERREVAL, H. (2010) Real time selection of scheduling rules and knowledge extraction via dynamically controlled data mining. *Int. J. Prod. Res.*, **48**, 6909–6938.
- MOHAMMAD NEZHAD, A. & MAHLOOJI, H. (2014) An artificial neural network meta-model for constrained simulation optimization. *J. Oper. Res. Soc.*, **65**, 1232–1244.
- MOHAN, T. R., ROSELYN, J. P., UTHRA, R. A., DEVARAJ, D. & UMACHANDRAN, K. (2021) Intelligent machine learning based total productive maintenance approach for achieving zero downtime in industrial machinery. *Comput. Ind. Eng.*, **157**, 107267.
- MOHANTY, M., SINGH, R. & SHANKAR, R. (2018) Improving the operational efficiency of outbound retail logistics using clustering of retailers and consumers. *J. Model. Manag.*, **13**, 646–674.
- MOSCOSO-LÓPEZ, J. A., TURIAS, I., JIMÉNEZ-COME, M. J., RUIZ-AGUILAR, J. J., CERBÁN, M. D. M. (2019) A two-stage forecasting approach for short-term intermodal freight prediction. *Int. Trans. Oper. Res.*, **26**, 642–666.
- MOURONTE-LÓPEZ, M. L. (2018) Optimizing the spare parts management process in a communication network. *J. Netw. Syst. Manag.*, **26**, 169–188.
- NAIR, D. J., RASHIDI, T. H. & DIXIT, V. V. (2017) Estimating surplus food supply for food rescue and delivery operations. *Socio-econ. Plan. Sci.*, **57**, 73–83.
- NEGHBAB, D. P., KHAYYATI, S. & KARAESMEN, F. (2022) An integrated data-driven method using deep learning for a newsvendor problem with unobservable features. *Eur. J. Oper. Res.*, **302**, 482–496.
- NEPAL, B. & YADAV, O. P. (2015) Bayesian belief network-based framework for sourcing risk analysis during supplier selection. *Int. J. Prod. Res.*, **53**, 6114–6135.
- NI, D., XIAO, Z. & LIM, M. K. (2020) A systematic review of the research trends of machine learning in supply chain management. *Int. J. Mach. Learn. Cybern.*, **11**, 1463–1482.
- NTABE, E. N., LEBEL, L., MUNSON, A. D. & SANTA-EULALIA, L.-A. (2015) A systematic literature review of the supply chain operations reference (SCOR) model application with special attention to environmental issues. *Int. J. Prod. Econ.*, **169**, 310–332.
- O'NEIL, S., ZHAO, X., SUN, D. & WEI, J. C. (2016) Newsvendor problems with demand shocks and unknown demand distributions. *Decis. Sci.*, **47**, 125–156.
- OROJLOOYADID, A., NAZARI, M., SNYDER, L. V. & TAKÁČ, M. (2022) A deep q-network for the beer game: deep reinforcement learning for inventory optimization. *Manuf. Serv. Oper. Manag.*, **24**, 285–304.

- OROŠNJAK, M., BRKLIJAČ, N., ŠEVIĆ, D., ČAVIĆ, M., OROS, D. & PENČIĆ, M. (2023) From predictive to energy-based maintenance paradigm: achieving cleaner production through functional-productiveness. *J. Clean. Prod.*, **408**, 137177.
- PAL, R., WANG, P. & LIANG, X. (2017) The critical factors in managing relationships in international engineering, procurement, and construction (IEPC) projects of chinese organizations. *Int. J. Proj. Manag.*, **35**, 1225–1237.
- PARK, H., CHOI, D. G. & MIN, D. (2023) Adaptive inventory replenishment using structured reinforcement learning by exploiting a policy structure. *Int. J. Prod. Econ.*, **266**, 109029.
- PEGADO-BARDAYO, A., LORENZO-ESPEJO, A., MUÑUZURI, J. & APARICIO-RUIZ, P. (2023) A data-driven decision support system for service completion prediction in last mile logistics. *Transp. Res. A: Policy Pract.*, **176**, 103817.
- PEREIRA, M. M. & FRAZZON, E. M. (2021) A data-driven approach to adaptive synchronization of demand and supply in omni-channel retail supply chains. *Int. J. Inf. Manag.*, **57**, 102165.
- PETROPOULOS, F., MAKRIDAKIS, S., ASSIMAKOPOULOS, V. & NIKOLOPOULOS, K. (2014) Horses for courses' in demand forecasting. *Eur. J. Oper. Res.*, **237**, 152–163.
- PREIL, D. & KRAPP, M. (2022) Bandit-based inventory optimisation: reinforcement learning in multi-echelon supply chains. *Int. J. Prod. Econ.*, **252**, 108578.
- PRESTWICH, S., TARIM, S., ROSSI, R. & HNIC, B. (2012) A neuroevolutionary approach to stochastic inventory control in multi-echelon systems. *Int. J. Prod. Res.*, **50**, 2150–2160.
- RAUT, R. D., KAMBLE, S. S., KHARAT, M. G., JOSHI, H., SINGHAL, C. & KAMBLE, S. J. (2017) A hybrid approach using data envelopment analysis and artificial neural network for optimising 3pl supplier selection. *Int. J. Logist. Syst. Manag.*, **26**, 203–223.
- REKABI, S., SAZVAR, Z. & GOODARZIAN, F. (2023) A machine learning model with linear and quadratic regression for designing pharmaceutical supply chains with soft time windows and perishable products. *Decis. Anal. J.*, **9**, 100325.
- ROHDE, J. (2004) Hierarchical supply chain planning using artificial neural networks to anticipate base-level outcomes. *OR Spectrum*, **26**, 471–492.
- ROLF, B., JACKSON, I., MÜLLER, M., LANG, S., REGGELIN, T. & IVANOV, D. (2023) A review on reinforcement learning algorithms and applications in supply chain management. *Int. J. Prod. Res.*, **61**, 7151–7179.
- ROSTAMI-TABAR, B., ARORA, S., RENDON-SANCHEZ, J. F. & GOLTSOS, T. E. (2024) Probabilistic forecasting of daily COVID-19 admissions using machine learning. *IMA J. Manag. Math.*, **35**, 21–43.
- SADOWSKI, A., SADOWSKI, M., ENGELSETH, P., GALAR, Z. & SKOWRON-GRABOWSKA, B. (2023) Using neural networks to examine trending keywords in inventory control. *Prod. Eng. Arch.*, **29**, 474–489.
- SALARI, N., LIU, S. & SHEN, Z.-J. M. (2022) Real-time delivery time forecasting and promising in online retailing: when will your package arrive? *Manuf. Serv. Oper. Manag.*, **24**, 1421–1436.
- SANDERS, N. R. (2024) The 'Inter-AI Period': how management mathematics can help shape an AI-enabled future. *IMA J. Manag. Math.*, **35**, 151–162.
- SASAKI, H. & SAKATA, I. (2021) Business partner selection considering supply-chain centralities and causalities. *Supply Chain Forum: An International Journal*, **22**, 74–85.
- SCARF, P., SYNTETOS, A. & TEUNTER, R. (2024) Joint maintenance and spare-parts inventory models: a review and discussion of practical stock-keeping rules. *IMA J. Manag. Math.*, **35**, 83–109.
- SCHNECKENREITHER, M., HAEUSSLER, S. & GERHOLD, C. (2021) Order release planning with predictive lead times: a machine learning approach. *Int. J. Prod. Res.*, **59**, 3285–3303.
- SCHOLTEN, K., STEVENSON, M. & VAN DONK, D. P. (2020) Dealing with the unpredictable: supply chain resilience. *Int. J. Oper. Prod. Manag.*, **40**, 1–10.
- SEURING, S. & MÜLLER, M. (2008) From a literature review to a conceptual framework for sustainable supply chain management. *J. Clean. Prod.*, **16**, 1699–1710.
- SGARBOSSA, F., ARENA, S., TANG, O. & PERON, M. (2023) Renewable hydrogen supply chains: a planning matrix and an agenda for future research. *Int. J. Prod. Econ.*, **255**, 108674.
- SHARMA, S. K. & GEORGE, S. A. (2021) A vendor recommendation model using neural networks. *Int. J. Process Manag. Benchmarking*, **11**, 254–270.

- SHARMA, R., KAMBLE, S. S., GUNASEKARAN, A., KUMAR, V. & KUMAR, A. (2020) A systematic literature review on machine learning applications for sustainable agriculture supply chain performance. *Comput. Oper. Res.*, **119**, 104926.
- SHCHERBAKOV, M. & SAI, C. (2022) A hybrid deep learning framework for intelligent predictive maintenance of cyber-physical systems. *ACM Trans. Cyber-Phys. Syst. (TCPS)*, **6**, 1–22.
- SINGH, L. P. & CHALLA, R. T. (2016) Integrated forecasting using the discrete wavelet theory and artificial intelligence techniques to reduce the bullwhip effect in a supply chain. *Glob. J. Flex. Syst. Manag.*, **17**, 157–169.
- SINGH, R. & MISHRA, V. K. (2023a) Inventory model using machine learning for demand forecast with imperfect deteriorating products and partial backlogging under carbon emissions. *Ann. Oper. Res.*, **335**, 361–383.
- SINGH, R. & MISHRA, V. K. (2023b) Machine learning based fuzzy inventory model for imperfect deteriorating products with demand forecast and partial backlogging under green investment technology. *J. Oper. Res. Soc.*, **75**, 1223–1238.
- SPILIOTIS, E., MAKRIDAKIS, S., SEMENOGLU, A.-A. & ASSIMAKOPOULOS, V. (2020) Comparison of statistical and machine learning methods for daily SKU demand forecasting. *Oper. Res.*, **22**, 3037–3061.
- SPILIOTIS, E., MAKRIDAKIS, S., KALTSOUNIS, A. & ASSIMAKOPOULOS, V. (2021) Product sales probabilistic forecasting: an empirical evaluation using the M5 competition data. *Int. J. Prod. Econ.*, **240**, 108237.
- SVOBODA, J. & MINNER, S. (2022) Tailoring inventory classification to industry applications: the benefits of understandable machine learning. *Int. J. Prod. Res.*, **60**, 388–401.
- SYNTETOS, A. A. & BOYLAN, J. E. (2001) On the bias of intermittent demand estimates. *Int. J. Prod. Econ.*, **71**, 457–466.
- SYNTETOS, A. A. & BOYLAN, J. E. (2005) The accuracy of intermittent demand estimates. *Int. J. Forecast.*, **21**, 303–314.
- SYNTETOS, A. A., BABAI, M. Z. & GARDNER JR., E. S. (2015) Forecasting intermittent inventory demands: simple parametric methods vs. bootstrapping. *J. Bus. Res.*, **68**, 1746–1752.
- TALWAR, S., KAUR, P., FOSSO WAMBA, S. & DHIR, A. (2021) Big data in operations and supply chain management: a systematic literature review and future research agenda. *Int. J. Prod. Res.*, **59**, 3509–3534.
- TAO, J., DAI, H., CHEN, W. & JIANG, H. (2023) The value of personalized dispatch in O2O on-demand delivery services. *Eur. J. Oper. Res.*, **304**, 1022–1035.
- THOMASSEY, S. (2010) Sales forecasts in clothing industry: the key success factor of the supply chain management. *Int. J. Prod. Econ.*, **128**, 470–483.
- THOUMMALA, N., KANG, Y. & MIN, D. (2023) A deep learning-based approach to a newsvendor problem considering uncertainty and time-varying costs. *Optim. Lett.*, **18**, 1963–1974.
- TIAN, Y.-X. & ZHANG, C. (2023) An end-to-end deep learning model for solving data-driven newsvendor problem with accessibility to textual review data. *Int. J. Prod. Econ.*, **265**, 109016.
- TIAN, Z., ZHONG, R. Y., VATANKHAH BARENJI, A., WANG, Y., LI, Z. & RONG, Y. (2021) A blockchain-based evaluation approach for customer delivery satisfaction in sustainable urban logistics. *Int. J. Prod. Res.*, **59**, 2229–2249.
- TOORAJIPOUR, R., SOHRABPOUR, V., NAZARPOUR, A., OGHAZI, P. & FISCHL, M. (2021) Artificial intelligence in supply chain management: a systematic literature review. *J. Bus. Res.*, **122**, 502–517.
- TSAI, P.-C. & HUANG, J.-Y. (2012) Two-stage replenishment policies for deteriorating items at taiwanese convenience stores. *Comput. Oper. Res.*, **39**, 328–338.
- TSAI, J.-M. & HUNG, S.-W. (2016) Supply chain relationship quality and performance in technological turbulence: an artificial neural network approach. *Int. J. Prod. Res.*, **54**, 2757–2770.
- TÜYLÜ, A. N. A. & EROĞLU, E. (2019) Using machine learning algorithms for forecasting rate of return product in reverse logistics process. *Alphanumeric J.*, **7**, 143–156.
- VAN DER GAAST, J. P. & WEIDINGER, F. (2022) A deep learning approach for the selection of an order picking system. *Eur. J. Oper. Res.*, **302**, 530–543.
- VAN HEZEWIJK, L., DELLAERT, N., VAN WOENSEL, T. & GADEMANN, N. (2023) Using the proximal policy optimisation algorithm for solving the stochastic capacitated lot sizing problem. *Int. J. Prod. Res.*, **61**, 1955–1978.
- VAN STEENBERGEN, R., MES, M. & VAN HEESWIJK, W. (2023) Reinforcement learning for humanitarian relief distribution with trucks and UAVs under travel time uncertainty. *Transp. Res. Part C Emerg. Technol.*, **157**, 104401.

- WANG, H., TAO, J., PENG, T., BRINTRUP, A., KOSASIH, E. E., LU, Y., TANG, R. & HU, L. (2022) Dynamic inventory replenishment strategy for aerospace manufacturing supply chain: combining reinforcement learning and multi-agent simulation. *Int. J. Prod. Res.*, **60**, 4117–4136.
- WILSON, V. H., NS, A. P., SHANKHARAN, A., KAPOOR, S. and RAJAN A, J. (2020) Ranking of supplier performance using machine learning algorithm of random forest. *Int. J. Adv. Res. Eng. Technol. (IJARET)*, **11**, 298–308.
- WU, C. & BARNES, D. (2012) A dynamic feedback model for partner selection in agile supply chains. *Int. J. Oper. Prod. Manag.*, **32**, 79–103.
- WU, C. & BARNES, D. (2014) Partner selection in agile supply chains: a fuzzy intelligent approach. *Prod. Plan. Control.*, **25**, 821–839.
- XIANG, C., WU, Z., ZHOU, Y. & TU, J. (2023) Dual-decoder attention model in hierarchical reinforcement framework for dynamic crowd logistics problem with batch-matching. *Transp. Res. Part C Emerg. Technol.*, **157**, 104417.
- YAN, Y., CHOW, A. H., HO, C. P., KUO, Y.-H., WU, Q. & YING, C. (2022) Reinforcement learning for logistics and supply chain management: methodologies, state of the art, and future opportunities. *Transp. Res. E Logist. Transp. Rev.*, **162**, 102712.
- YANG, A., QIU, Q., ZHU, M., CUI, L., CHEN, W. & CHEN, J. (2022) Condition-based maintenance strategy for redundant systems with arbitrary structures using improved reinforcement learning. *Reliab. Eng. Syst. Saf.*, **225**, 108643.
- YASIR, M., ANSARI, Y., LATIF, K., MAQSOOD, H., HABIB, A., MOON, J. & RHO, S. (2022) Machine learning–assisted efficient demand forecasting using endogenous and exogenous indicators for the textile industry. *Int. J. Logist. Res. Appl.*, in press. <https://doi.org/10.1080/13675567.2022.2100334>.
- ZHANG, X. (2004) The impact of forecasting methods on the bullwhip effect. *Int. J. Prod. Econ.*, **88**, 15–27.
- ZHANG, G. P., XIA, Y. & XIE, M. (2023) Intermittent demand forecasting with transformer neural networks. *Ann. Oper. Res.*, **339**, 1051–1072.
- ZHAO, Z. & LIANG, Y. (2023) A deep inverse reinforcement learning approach to route choice modeling with context-dependent rewards. *Transp. Res. Part C Emerg. Technol.*, **149**, 104079.
- ZHAO, H., SUN, S. & JIN, B. (2018) Sequential fault diagnosis based on LSTM neural network. *IEEE Access*, **6**, 12929–12939.
- ZHONG, R. Y., XU, X., KLOTZ, E. & NEWMAN, S. T. (2017) Intelligent manufacturing in the context of Industry 4.0: a review. *Engineering*, **3**, 616–630.
- ZHU, X., NINH, A., ZHAO, H. & LIU, Z. (2021) Demand forecasting with supply-chain information and machine learning: evidence in the pharmaceutical industry. *Prod. Oper. Manag.*, **30**, 3231–3252.
- ZHUANG, X., YU, Y. & CHEN, A. (2022) A combined forecasting method for intermittent demand using the automotive aftermarket data. *Data Sci. Manag.*, **5**, 43–56.
- ZOU, Y., WU, H., YIN, Y., DHAMOTHARAN, L., CHEN, D. & TIWARI, A. K. (2022) An improved transformer model with multi-head attention and attention to attention for low-carbon multi-depot vehicle routing problem. *Ann. Oper. Res.*, **339**, 517–536.

Appendix. List of acronyms

AI: artificial intelligence; ANFIS: adaptive neuro-fuzzy inference system; ANN: artificial neural networks; AUSVM: adaptive univariate support vector machine; CBM: condition based maintenance; DEA: data envelopment analysis; DL: deep learning; DPFNN: double parallel feedforward network; DT: decision tree; DTR: decision tree regression; GA: genetic algorithm; GBT: gradient boosting trees; GRNN: general regression neural network; KNN: K-nearest neighbors; LR: logistic regression; LSR: least square regression; ML: machine learning; MR: multiplicative regression; NN: neural network; PCR: principal component regression; PLSR: partial least squares regression; RF: random forest; RT: regression tree; RUL: remaining useful life; SCM: supply chain management; SR: semilogarithmic regression; SVM: support vector machine; SVR: support vector regressor.

