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# Machine Learning in Supply Chain Management: A Scoping Review

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# Machine Learning in Supply Chain Management: A Scoping Review

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***Purpose:*** *Especially in supply chain management (SCM), data has become essential to the success of companies. Traditional analytical methods are being augmented by machine learning (ML), which is considered the foremost relevant branch of artificial intelligence. This article maps various ML use-cases and assigns them to the appropriate SCM tasks.*

***Methodology:*** *We applied a scoping review and checked scientific databases for relevant literature. Subsequently, the articles were assigned to different categories to map the research area. In the categorization, we considered, amongst others, the ML tasks and algorithms, data source and type, and the field of application.*

***Findings:*** *The results show that there are numerous ML use cases in SCM. These range from predictive demand forecasting and intelligent partner selection to the use of assistance systems for resource management. Various data sources, such as internal company data and publicly available data, are used for these applications.*

***Originality:*** *By mapping ML use cases in SCM, this complex and multifaceted field of research is presented in a transparent and structured way. Science and practice can deploy the results to improve existing ML use cases in SCM on the one hand and to identify promising areas of application on the other.*

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# 1. Introduction

A particularly important and ongoing topic in supply chain management (SCM) is the need to make complex decisions. Furthermore, supply chains are plagued by uncertainty and information asymmetry. In other words, on the one hand, decision-making processes in SCM depend on diverse, non-influenceable factors that are currently often influenced by information barriers (Ni, Xiao, and Lim, 2020, p. 1463). On the other hand, the volume and variety of data are constantly increasing, and there is more data available than ever before. Analyzing this data with the use of traditional methods is inefficient, or even impossible, in most cases. For this reason, new methods and applications are emerging from the field of advanced data analytics (ADA). One of these methods is machine learning (ML), which deals with the development and application of self-learning algorithms (Marsland, 2014, pp. 6-9; Wenzel, Smit, and Sardesai, 2019).

ML has proven to be particularly capable of coping with large amounts of data and detecting patterns in the data. This property enables ML to make reliable decisions that humans are not capable of. Moreover, ML algorithms enable users to deal with rapidly changing conditions and discontinuous information. Thus, ML is a significant asset for SCM (Ni, Xiao, and Lim, 2020, p. 1463). Kersten et al. (2020) confirm this assumption and show the potential of ADA, and, thus, also ML, in SCM. Companies can particularly benefit from ML in the areas of planning, procurement, and delivery (Kersten et al., 2020).

However, how is ML applied in SCM to make complex decisions related to uncertainties? The research goal of this article is to answer the following question:

> *“What is the current state of research on the use of machine learning in supply chain management?”*

The remainder of this article is organized as follows. Chapter 2 describes the methodological approach and distinguishes this article from the current state of research. Chapter 3 includes the classification of the identified literature in terms of publication type, SCM task, industry focus, related data sources and types, and applied ML algorithms. Chapter 4 answers the underlying research question and identifies further research needs. Finally, Chapter 5 summarizes the results.

# 2. Methodological Approach

Systematic literature reviews (SLR) are used in a wide range of research areas (Arksey and O'Malley, 2005). SLRs originated in the field of medicine. Later, Tranfield, Denyer, and Smart (2003) adapted SLRs to the needs and characteristics of management research and Durach, Kembro, and Wieland (2017) to those of SCM research. These adaptations are necessary because each research area has different requirements and characteristics (Durach, Kembro, and Wieland, 2017, p. 68). Currently, scoping reviews, which also follow a systematic approach, are becoming increasingly important for the aim of a synthesis (Munn et al., 2018). However, SLRs and scoping reviews have different objectives. Therefore, researchers should carefully determine which of the two procedures is appropriate to achieve their individual research objectives (Arksey and O'Malley, 2005). If, on the one hand, the research objective is to analyze the feasibility, appropriateness, usefulness, or effectiveness of specific practices, then an SLR is particularly well-suited to achieve the research objective. If, on the other hand, the research goal is to identify specific concepts and to present, report, or discuss those concepts, a scoping approach should be used (Munn et al., 2018, p. 144). Since the research objective of this article is to address the current state of research on the application of ML in SCM, the scoping review approaches of Arksey and O'Malley (2005) and Levac, Colquhoun, and O'Brien (2010) were chosen as the methodological foundation of this article.

The following section describes the search and selection process for the scoping review to ensure that the research process is transparent. Furthermore, a differentiation of this research from the current state of research is presented to emphasize the unique research insights of this review.

## 2.1 Search and Selection Process

According to Arksey and O'Malley (2005), scoping reviews assist in rapidly capturing the key concepts of a research area, especially when the area is complex or has not yet been analyzed. In addition, research gaps and designs can be identified and analyzed, or the macroscopic view can lay the groundwork for a further SLR (Munn et al., 2018, p. 144). Arksey and O'Malley (2005) and Levac, Colquhoun, and O'Brien (2010) described five steps for conducting a scoping review. Figure 1 shows the step-by-step process of the conducted scoping review.

1) Identify the research question – The underlying research question for this paper is "What is the current state of research on the use of machine learning in supply chain management?" It was formulated by the authors to achieve the research objective of this paper.

2) Identify relevant studies – To identify relevant articles, the online databases Scopus, Web of Science, ScienceDirect and IEEE Xplore were selected. Specific search terms were determined, divided into two distinct word groups, and meaningfully related using Boolean operators for the targeted search for the relevant articles. The first word group included "machine learning" and the second word group "supply chain" or appropriate synonyms. The literature search was performed on January 1, 2021, with a search for a combination of the two word groups in the title, abstract, and keywords of the articles. Thus, an initial literature set of 1,878 articles were identified.

3) Study selection – The selection of relevant studies from the initial literature set included duplicate screening, abstract screening, and full text screening. Since the literature was retrieved from multiple databases, some articles were found to be duplicates, and these were removed during the duplicate screening process. Thus, the initial literature set was reduced from 1,878 to 1,145 articles. The abstracts of the articles were evaluated according to previously determined inclusion criteria, according to ten Hompel and Hellingrath (2007) and ten Hompel, et al. (2013). In addition, the ML method used in the article must involve one or more ML algorithms, according to Marsland (2014). Thus, the relevant articles could be further narrowed down, from 1,145 to 497. In the next step, full text screening was done. The previously mentioned inclusion criteria were used, but the full text of the articles was screened for relevance. After the full text screening, 183 articles were classified as relevant. In a further step, a search for additional literature was undertaken with Wohlin's (2014) snowballing approach. For this purpose, 14 literature reviews previously identified during the study selection process were examined to identify additional relevant literature. With consideration of the same inclusion criteria, 79 articles were added to the literature set. Finally, 262 articles that address ML algorithms in the SCM context were identified.

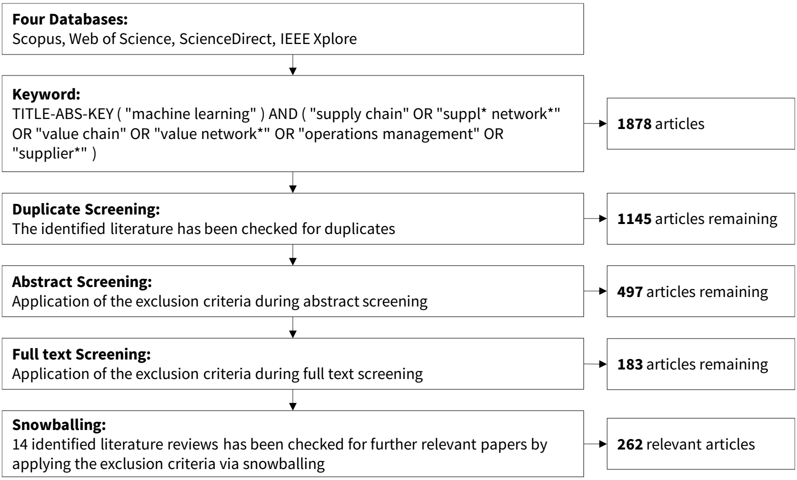


Figure 1: Methodological approach for the scoping review, following Arksey and O'Malley (2005) and Levac, Colquhoun, and O'Brien (2010).

The next steps, according to Levac, Colquhoun, and O'Brien (2010), are 4) charting the data and 5) collating, summarizing, and reporting results. charting the data means classifying the data according to previously determined classes. The resulting classification is then analyzed, and the results presented descriptively. Collating, summarizing, and reporting results are done to provide an overview of the scope of the literature, but not in the form of a synthesis. Instead, a numerical analysis is done, presenting, for example, the scope and nature of the studies with the use of tables and charts. The scoping review is concluded with a thematic analysis. Steps 4 and 5, following Arksey and O'Malley (2005) and Levac, Colquhoun, and O'Brien (2010), are conducted in detail later in the article.

## 2.2 Related Studies

As mentioned above, 14 literature reviews that had an objective comparable to that of this article were identified during the search and selection process. All 14 identified articles focus on the applications of ML or artificial intelligence in the logistics or SCM context. The main differences are in terms of the time periods considered, the research methods applied, the consulted databases, and the search terms used. The primary difference of this article, aside from its topicality, is the research method. The identified articles were all literature reviews, but not all were SLRs. However, none of the reviews followed the approach of a scoping review and the accompanying systematic quantitative analysis and interpretation of the research findings. Table 1 shows the 14 identified literature reviews and their respective focus topics.

Table 1: Identified literature reviews

| No. | Authors | Focus of literature reviews |
|---|---|---|
| 01 | Bousqaoui, Achchab, and Tikito (2017) | Supply Chain Management |
| 02 | Burggraf, Wagner, and Koke (2018) | Production Management |
| 03 | Cadavid, Lamouri, and Grabot (2018) | Demand & Sales Forecasting |
| 04 | Hachimi, Oubrich, and Souissi (2018) | Reverse Logistics |
| 05 | Nguyen et al. (2018) | Supply Chain Management |
| 06 | Baryannis et al. (2019) | Supply Chain Risk Management |
| 07 | Calatayud, Mangan, and Christopher (2019) | Supply Chain Management |
| 08 | Diez-Olivan et al. (2019) | Industrial Applications |
| 09 | Ni, Xiao, and Lim (2020) | Supply Chain Management |
| 10 | Wenzel, Smit, and Sardesai (2019) | Supply Chain Management |
| 11 | Hosseini and Ivanov (2020) | Supply Chain Risk Management |

| No. | Authors | Focus of literature reviews |
|---|---|---|
| 12 | Kumar et al. (2020) | Distribution Planning |
| 13 | Seyedan and Mafakheri (2020) | Demand Forecasting |
| 14 | Aamer, Yani, and Priyatna (2020) | Demand Forecasting |

# 3. Classification of Articles

In the following section, the 262 identified articles are classified in terms of year of publication, publication type, SCM task, industry focus, related data sources and types, and ML algorithm applied to provide a comprehensive picture of the current state of research into ML in SCM.

## 3.1 Year and Type of Publication

If we examine the number of publications over time, as depicted in Figure 2, it is notable that there is a sharp increase. The first noticeable increase was in 2005, when six articles on the topic of ML in SCM were published. By 2015, with the exception of some fluctuation, the number of publications per year had more than doubled, from six to 17. The most interesting development in terms of the absolute number of publications is evident during the period from 2015 to 2020. After a decrease from 17 publications in 2016 to 11 in 2017, there was rapid increase during the following two years. During 2019, 60 papers were published. ML in SCM seems to have gained importance, which can be related to the increasing amount and importance of data in research and in practice (Kersten et al., 2020). The decrease in the number of publications in 2020 and 2021 can be explained by the fact that, as described in Subchapter 2.1, the literature search was conducted on January 1, 2021, and not all submitted and published articles had yet been entered into the databases.

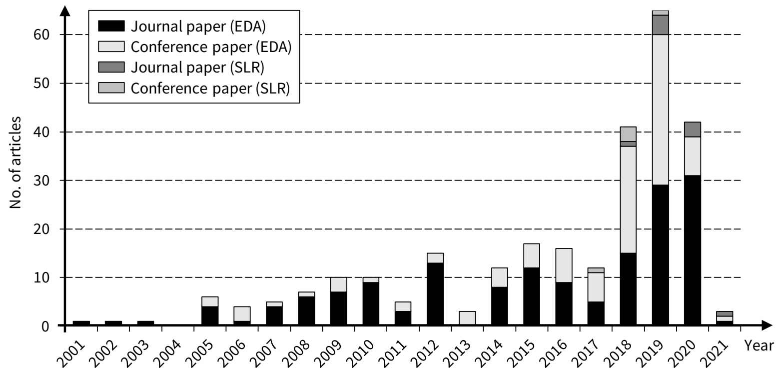


Figure 2: Classification in relation to the year of publication

In addition to the number of publications, it is worth investigating the types of publications and research methods used over time. First, we distinguished between journal and conference papers that applied exploratory data analysis (EDA) related to ML to evaluate historical-empirical data. In the early 2000s, authors mostly published in journals, which illustrates the strong connection between this topic and academia. In 2005, the ratio of journal articles to conference papers was four to two, and the number of journal articles continued to increase through 2012, when there was a ratio of 13 to two. These numbers reinforce the scientific importance of ML in SCM. As of 2014, there was a change in terms of publication type. The ratio of journal to conference papers changed from 13 to two in 2012 to 29 to 31 in 2019. This change in the publication ratio can be partially attributed to the fact that the requirements are less stringent and the publication timeframe shorter for conference papers compared to journal articles. Authors working on the topic of ML in SCM seem to want to publish their new findings and results as soon as possible in the scientific communities. As previously mentioned, the literature was retrieved from scientific databases on January 1, 2021, and, therefore, presents a distorted view of the publication ratio for 2020 and 2021.

There was an additional finding relating to publication types and research methods. In 2017, the first article that used an SLR as a research method, in which Bousqaoui, Achchab, and Tikito (2017) investigated how ML is applied in SCM, was published. Over the following years, more journal and conference papers that conducted SLRs were added. Since then, the number of publications has steadily increased. SLRs help to identify research gaps (Munn et al., 2018). In addition to the emergence of a research method, there is another observation worth highlighting in this context; compared to papers that applied EDA, SLRs were initially presented at conferences rather than published in journals. The first journal papers that involved an SLR methodology were published in 2018. This is one year after the first conference paper was presented. Due to this fact, the scientific relevance of ML in SCM can be emphasized again, as it is well known in the scientific environment that SLRs tend to be more difficult to publish in journals than papers involving other research methods, but, nevertheless, the number of SLRs in journals is steadily increasing.

Especially in recent years, scientists tend to present their results at conferences and, thus, through a rapid publication channel. In addition to EDA, SLR has become an effective and scientifically accepted research method.

## 3.2 Supply Chain Management Tasks

The following subsection analyzes the SCM tasks in which ML is applied. The investigation is based on the SCM task model by ten Hompel et al. (2013). Figure 3 shows the distribution of the 262 identified articles in relation to the SCM tasks. A detailed assignment of the articles to the individual SCM tasks can be found in the online appendix[1] of this article. Specific criteria for the classification and assignment of the articles were derived from an evaluation of the SCM tasks described by ten Hompel et al. (2013) and ten Hompel and Hellingrath (2007). It should be noted that individual items can be assigned to multiple SCM tasks. In their SCM task model, ten Hompel et al. (2013) distinguish between the SCM tasks supply chain design (SCD), supply chain planning (SCP), supply chain execution (SCE), collaborative tasks, and complementary tasks on

[1]Online appendix: https://www.researchgate.net/profile/Martin-Brylowski-2/research

the macroscopic level. In some cases, these higher-level SCM tasks are broken down into further SCM subtasks. The complementary tasks are not considered further in this article, as none of the identified items could be assigned to this SCM task.

The task of SCD involves long-term planning regarding the logistical strategy, partner selection, and location issues (ten Hompel et al., 2013, p. 148). A total of 70 of the 248 identified articles could be assigned to SCD. These included the SCM subtasks, with seven articles assigned to supply chain strategy, 54 to partner selection, one to facility selection, three to sourcing process design, and seven articles were assigned to design of communication and information processes. It became clear from this analysis that, from a scientific point of view, partner selection especially benefits from ML. ML algorithms are applied to find potential partners (Handfield, Sun, and Rothenberg, 2020), evaluate them (Sasaki and Sakata, 2020), and, subsequently, selects the appropriate partners (Wu et al., 2020).

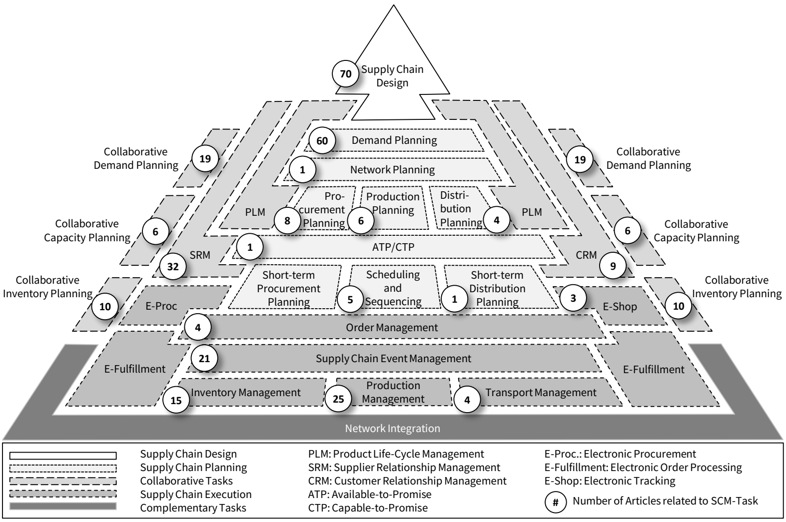


Figure 3: Classification in relation to SCM tasks,
based on Ten Hompel et al. (2013) and Ten Hompel and Hellingrath (2007)

The term SCP includes all medium-term planning tasks of a company, as well as deriving customer requirements (ten Hompel et al., 2013, p. 149). A total of 81 of the 248 items could be assigned to SCP. Of these, 60 were assigned to demand planning, one to network planning, eight to procurement planning, six to production planning, four to distribution planning, one to available-to-promise/capable-to-promise, five to scheduling and sequencing, and one to short-term distribution planning. One SCM subtask in the planning task area is particularly dominant compared to the others. ML is used far more in demand planning and support, for example, for the prediction of future customer requirements and supply chain performance (Feizabadi, 2020) or the timely provision of spare parts for customers (Babajanivalashedi et al., 2018).

The SCE area is dedicated to transport-related tasks, the network-wide scheduling of customer orders, and the monitoring of inventories (ten Hompel et al., 2013, p. 154). In total, 67 of the 248 identified articles were assigned to SCE tasks. Order management was represented by four articles, supply chain event management by 21, inventory management by 15, production management by 25, and, finally, transportation management by four articles. Compared to SCD and SCP, no one SCM subtask is particularly dominant in SCE, which suggests that ML is used more for many purposes in operational SCM tasks, and different areas benefit equally from self-learning algorithms. For example, ML is used for quality monitoring in supply chain event management (Myles D., Steven and Sengun, 2015), for ABC classification of products in inventory management (Li, Moghaddam and Nof, 2016), and for automatic defect detection in additive manufacturing processes in production management (Okaro et al., 2019).

According to ten Hompel and Hellingrath (2007, p. 299), a logistics network can only be harmonized and supply optimally synchronized with cross-company cooperation. In addition to collaborative demand planning, collaborative capacity planning, and collaborative inventory planning, supply relationship management and customer relationship management were also assigned to collaborative tasks in this article. This is due to the cross-enterprise activities of the two SCM subtasks. In total, 72 of the 248 identified articles were assigned to collaborative tasks. Nineteen of the articles address ML applications in collaborative demand planning, six in collaborative capacity planning, ten in collaborative inventory planning, 32 in supplier relationship management, and nine in customer relationship management. As in SCE, several SCM subtasks stand out in the collaborative task area. These include, for example, cross-network analysis and the determination of customer needs (Kilimci et al., 2019) and risk-based planning of inventory across the supply chain (Ojha et al., 2018). The SCM sub-task supplier relationship management stands out somewhat from the other collaborative tasks with 32 articles. These tasks include the control of existing supplier relationships (Wilson et al., 2020) and a classification of the supplier base (Sabbagh and Ameri, 2020). It can be concluded from this that ML algorithms have great potential in not only the search for, evaluation of, and selection of potential suppliers but also in the control of existing suppliers.

In summary, ML is used particularly frequently for SCM tasks related to improving cross-enterprise collaboration with suppliers and customers. In addition, ML is also widely used for operational SCM tasks to monitor or improve production processes.

## 3.3 Industry Focus

The classification of the articles in relation to the targeted industry was based on the International Standard Industrial Classification of All Economic Activities (ISIC) classification system of the United Nations (2008). Thus, a comprehensible and consistent classification of the articles is possible by following concrete concepts, definitions, principles, and classification rules (United Nations, 2008, p. 3). Figure 4 visualizes the classification of the identified articles in relation to the focused industry. First, the articles were assigned to the superordinate ISIC classes manufacturing, transportation and storage, wholesale and retail, and no reference to industry. This was followed by a detailed assignment to the subclasses of the ISIC classification system.

It was noticeable that most of the articles examine questions and problems from the manufacturing sector. One hundred and seventy-seven of the 262 articles could be assigned to the manufacturing industry. The most frequent subclasses are manufacturing without industrial focus (33 articles), data processing equipment (29 articles), motor vehicles and parts (27 articles), and food and feed products (25 articles). For example, Cavalcante et al. (2019) addressed resilient supplier selection without reference to a specific manufacturing industry. Wang and Chen (2020) make cross-company and collaborative forecasts for the manufacturing of printed circuit boards. Related to the manufacturing industry of motor vehicles and parts, Hong et al. (2018) addressed the identification of strategic value chain partners for the manufacturing of products for the automotive industry. In the manufacturing industry of food and feed products, Zakeri et al. (2018) developed a system for proactive monitoring of raw milk quality.

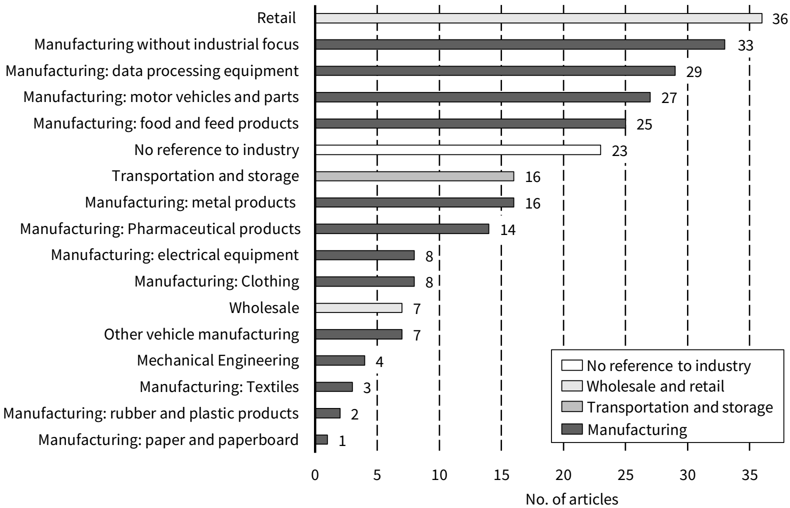


Figure 4: Classification in relation to the industry focus based on ISIC (United Nations, 2008)

The second most-addressed industry was wholesale and retail, with 43 identified articles, 36 relating to retail and 7 to wholesale. Pereira and Frazzon (2020) developed a method to synchronize demand in supply chains in retail. Priore et al. (2019) show how replenishment tasks can be dynamically determined in wholesale.

The transportation and storage industry sector accounted for 16 of the identified articles. Thus, it ranks third in terms of the most frequently addressed industry sector. In their article, Zhang, Li, and Peng (2020) demonstrate how risks in the transportation of fresh products can be assessed and monitored.

The remaining 23 articles were assigned to the class “No reference to industry” because, as the designation indicates, they include no references to an industry, according to ISIC. The analysis of the identified articles related to ISIC industries showed that manufacturing as well as wholesale and retail particularly benefit from ML in the context of the various SCM tasks.

## 3.4 Data Sources and Types

ML applications or EDA require data that is available in structured or unstructured forms (Marsland, 2014, p. 6). Ideally, however, a high quantity of data should be available, it should be of high quality, and it should be both diverse and granular (Kersten et al., 2020). Therefore, in the following section, we first classify the identified articles in terms of the data sources used, following Ni, Xiao, and Lim (2020), which is followed by a classification of the articles in terms of the data types considered, following Seyedan and Mafakheri (2020).

As previously mentioned, ML applications require data for analysis (Marsland, 2014, p. 6). This data can be obtained from a wide variety of data sources as Ni, Xiao, and Lim (2020) describe in their literature review. Figure 5 shows the data sources that were used to examine the problems in the different SCM tasks in the 262 identified articles.

One hundred and fifty-three of the identified articles used historical data provided by companies for scientific research. Baryannis, Dani, and Antoniou (2019) used historical data provided by several companies in a manufacturing aerospace supply chain over a six-year period to predict supply chain risks. Furthermore, 47 articles used publicly available data for their research. One example is Wichmann et al. (2020), who generated supply chain maps using news articles. Twenty-seven of the identified articles analyzed data from laboratories with ML algorithms. Alfian et al. (2020) deserve a mention as a striking example with their perishable food traceability system, based on internet of things sensors and ML algorithms. A total of 25 articles included interviews with experts to generate or verify data. Badurdeen et al. (2014) developed a supply chain risk taxonomy, which was subsequently incorporated into the ML analysis, through expert interviews. Finally, 11 of the identified articles used simulation data and 10 used data from other articles.

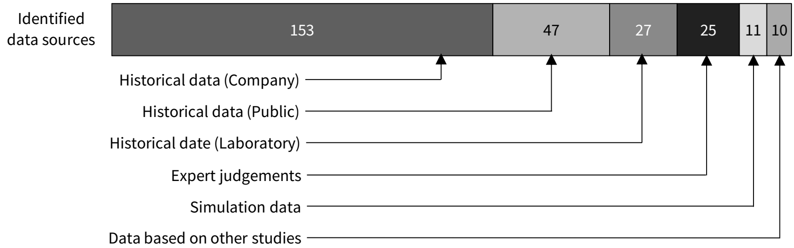


Figure 5: Classification in relation to data source, following Ni, Xiao, and Lim (2020)

Companies seem to have recognized the potential of ML in SCM and, therefore, make their data available for scientific analysis. In addition, publicly available data is often used in analyses with ML to gain new insights in the research area of SCM.

In addition to the data source, the data type also plays a significant role in the application of ML in SCM. Following Seyedan, and Mafakheri (2020), Figure 6 shows the data types that were used in the 262 identified articles for the ML analyses. It is noticeable that most of the data types include information regarding external partners or were sourced from operational SCM task areas. Seventy-seven articles used supplier data and interpreted it with ML. Brintrup et al. (2019) analyzed supplier-related data to predict supplier disruptions in the manufacture of complex equipment. Gružauskas, Gimžauskienė, and Navickas (2019) provide another example of using data that includes information about external partners. They evaluated sales-related data to evaluate the predictive accuracy of logistics cluster activities. A total of 51 articles used sales-related data for ML analyses. Demand data was analyzed in 49 articles in total. Bhosekar and Ierapetritou (2021) developed a framework for supply chain optimization in modular production, using demand data. A final class that should be mentioned in the context of data types that include information regarding external partners is customer data. Twenty-eight articles were assigned to this class, including Simeone, Zeng, and Caggiano (2020), who evaluated customer data for decision making to recommend manufacturing solutions in a cloud environment. In addition, data types from operational SCM tasks play a significant role in SCM. There were 41 articles that used manufacturing data for ML analysis. González Rodríguez, Gonzalez-Cava, and Méndez Pérez (2019) used production-related data for ML-based production planning, and 39 articles evaluated inventory data to make predictions regarding backorders (Hajek and Abedin, 2020). Furthermore, 26 articles explored the use of sensor data in the SCM context. For example, Ma, Wang, and Wang (2018) evaluated RFID sensor data with ML to detect false-positive decisions. Finally, product-related data was evaluated in 25 articles. In this context, Zgodavova et al. (2020) interpreted product-related data to improve small batch production systems.

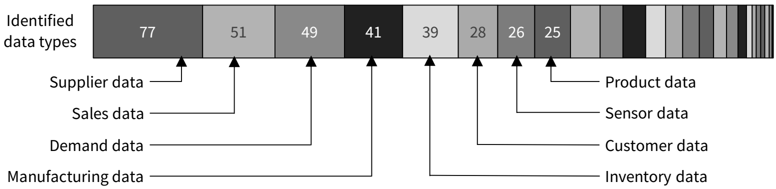


Figure 6: Classification in relation to data types following Seyedan and Mafakheri (2020).

In summary, data containing information regarding external partners, such as suppliers and customers, is particularly likely to be used for ML-based analysis to make strategic decisions in the SCM context. In addition, the application of ML in operational SCM task areas lead to improved processes. Particularly production and logistics-related data types are frequently examined for this purpose.

## 3.5 Machine Learning Algorithms

In addition to the data source and type, the choice of the optimal algorithm plays an essential role in ML applications. Marsland (2014) distinguishes between supervised, unsupervised, and reinforcement learning. Supervised learning refers to the analysis of structured input data and can be further differentiated to classification and regression algorithms (Marsland, 2014, p. 6). On the one hand, regression algorithms are primarily used for forecasts and to predict the course of data points (Marsland, 2014, pp. 6-8). Classification algorithms, on the other hand, assign defined classes to data and bundle them based on previously learned rules (Marsland, 2014, pp. 8-9).

Unsupervised learning algorithms work with unstructured data and independently attempt to detect unknown patterns in the data to, for example, subsequently cluster them or to detect anomalies (Marsland, 2014, p. 6).

Reinforcement learning approaches are a hybrid of supervised and unsupervised learning. When the algorithm makes incorrect decisions, it is corrected, but it does not learn the solution. This process continues until the algorithm has independently derived the optimal solution through trial and error (Marsland, 2014, p. 6).

Figure 7 illustrates the classification of the identified articles and use cases in terms of the ML algorithms used, according to Marsland (2014), on the vertical axis and the underlying SCM tasks, according to ten Hompel et al. (2013) and ten Hompel and Hellingrath (2007), on the horizontal axis. In the remainder of this article, we first describe articles that use supervised learning algorithms for ML-based analysis. This is followed by examples of unsupervised learning and, thereafter, articles from the reinforcement learning class.

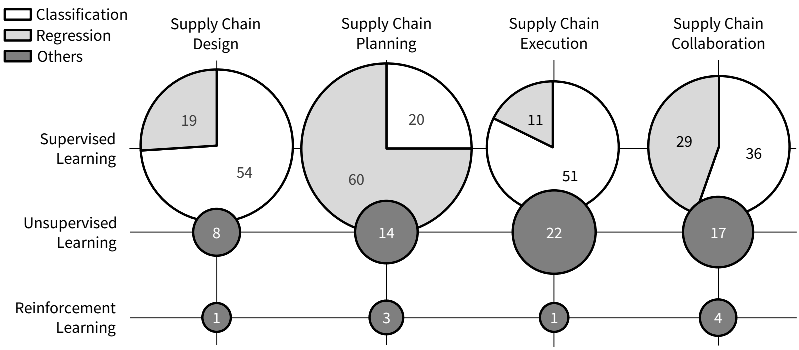


Figure 7: Classification in terms of algorithms following Marsland (2014); Ten Hompel et al. (2013) and Ten Hompel and Hellingrath (2007).

A total of 54 of the identified articles could be assigned in the classification algorithms class in the SCD. Harikrishnakumar et al. (2019) used classification algorithms to classify suppliers. ML applications that can be assigned to the regression class in the SCD are represented by 19 articles. For example, Brintrup et al. (2019) used regression algorithms to predict supplier risks. In the SCP task area of SCM, 20 articles used classification algorithms and 60 articles used regression algorithms. González Rodríguez, Gonzalez-Cava, and Méndez Pérez (2019) used classification algorithms for intelligent production planning in the SCP task area, and Priyadarshi et al. (2019) addressed the prediction of vegetable demand using regression analysis. In the SCE task area of SCM, 51 articles that applied classification algorithms for ML based analysis were identified. However, 11 articles applied regression algorithms for operational SCE tasks. In this context, Ahmadi, Javidi, and Shahbazmohamadi (2018) are worth mentioning because they used classification algorithms to identify counterfeits in the electrical industry. Amirkolaii et al. (2017) showed the potential of regression algorithms for predicting the demand of spare parts in the aerospace industry. Finally, in terms of supervised learning algorithms, in the SCC task domain, 36 articles could be assigned to the classification algorithms and 29 to the regression algorithms. In the collaborative SCM task domains, 36 articles describe the use of ML-based classification algorithms and 29 describe the use of regression algorithms. Illustrative examples include Abdollahnejadbarough et al. (2020), with their classification approach for supplier base rationalization, and Li et al. (2020), with their regression approach for sustainable production capacity assessment.

In addition to the supervised learning algorithms, articles that followed an unsupervised learning approach were also identified in all SCM task areas. In SCD, a total of eight articles followed an unsupervised learning approach. For example, Khalid and Herbert-Hansen (2018) showed how international location decisions can be made with clustering algorithms. In the tactical SCP, 14 articles could be identified. In this context, Meiners et al. (2019) investigated how production ramp-up can be accelerated and relationships in the process chain can be derived. There were 22 articles in the operational SCE domain. Becker and Intoyoad (2017) demonstrated how information on logistics processes can be extracted using ML in a data-based manner. Finally, 17 articles were assigned to collaborative SC tasks (SCC). Sabbagh and Ameri (2018) developed an ML approach to cluster suppliers based on unstructured production data.

As previously mentioned, it was also possible to identify articles that used reinforcement algorithms for ML-based analysis. One article that could be assigned to the SCD is by Zhang and Bhattacharyya (2007), who determined the design of a supply network. From the SCP domain, three articles could be identified. Vanvuchelen, Gijsbrechts, and Boute (2020) developed an approach to solve joint replenishment problems using deep reinforcement. In the SCM task domain SCE, similar to SCD, one article could be identified. Döring, Dangelmaier, and Danne (2007) applied reinforcement learning to production systems in the automotive industry. Finally, four articles were identified in the SCC context. Peng et al. (2019) are investigated the prediction of supply chain wide capacity under uncertainty.

In summary, with the supervised learning algorithms in the SCD and SCE task domains, significantly more classification algorithms are used than regression algorithms. In the SCP domain, the opposite effect can be seen. In the SCC, classification and regression analyses are almost equally distributed. Unsupervised learning algorithms, however, are primarily used in the SCE domain. The SCM tasks SCP and SCC form the middle field in unsupervised learning context. In SCD, unsupervised learning is uncommon. Reinforcement learning does not seem to be used frequently in the SCM context in general and is rather underrepresented in all SCM task domains, compared to supervised and unsupervised learning approaches.

# 4. Discussion and Further Research

Data analytics and ML are becoming increasingly relevant, especially in the SCM context (Kersten et al., 2020). Therefore, the research objective of this article was to analyze for which specific SCM tasks ML is applied. To achieve this research goal, the following research question was derived and answered progressively throughout this article through the analysis of the identified articles in a scoping review, based on Arksey and O'Malley (2005) and Levac, Colquhoun, and O'Brien (2010):

> *"What is the current state of research on the use of machine learning in supply chain management?"*

In the remainder of this article, the core findings of this work are discussed, and two recommendations for further research that could examine the topic of ML in SCM from a new direction in terms of methodology and content are provided.

First, it is worth mentioning that only articles using EDA or SLR as research methods were identified. These articles either describe the detailed implementation of ML algorithms in the SCM context (EDA) or provide a systematic overview of the current state of research (SLR). Qualitative interview studies, quantitative surveys, or conceptual papers on ML in SCM describing, for example, procedural models for the step-by-step and situation-appropriate implementation of ML in the different SCM task areas, could not be identified for this scoping review.

Three main application areas for ML in SCM emerged in this scoping review. These areas are supplier management, which can be assigned to the SCM task areas SCD and SCC, demand management, which is predominantly applied in SCP and SCC, and quality management, that can be assigned to SCE. Articles that involved ML analyses in the main application areas of supplier and demand management often used structured data that contain cross-company information regarding external SC partners, such as supplier-, sales-, and demand-related data. It is worth mentioning that supplier management is almost exclusively considered in the context of the manufacturing industry, and ML applications in demand management are more prevalent in the wholesale and retail sector. Furthermore, supplier management and demand management differ in terms of the ML algorithms used. Articles on the topic of supplier management generally use classification algorithms, and ML applications on the topic of demand management use regression algorithms. In quality management, production, product, and sensor data are analyzed, often with structured data in combination with unstructured data. Both supervised and unsupervised algorithms are used. The three main application areas identified, supplier management, demand management, and quality management, differ fundamentally in terms of the industry addressed, data source, data types, and ML algorithms. Future work should explore the three identified main application areas for ML in SCM in detail, in terms of industry, data source, data type, and ML algorithms.

## 5. Conclusion

From this review, it can be concluded that ML in SCM has gained relevance over recent years, as the number of publications has increased. ML is frequently used for cross-company SCM tasks to improve collaboration with suppliers and customers or to monitor internal processes, identify weak points, and initiate mitigation activities in a timely manner. Manufacturing companies and retailers are particularly likely to make their data available to academia, which can be evidenced by the high number of articles relating to these industries, thus exploiting the potential of ML to improve their strategic, tactical, operational, and collaborative SCM processes. Publicly available data is brought in by researchers to generate further value-adding insights and, thus, enhance the performance of ML algorithms in the SCM context. The data types most frequently used include information about suppliers or customers as well as information from the production environment or warehousing. This again underpins the relevance of ML in terms of strategic cross-company as well as tactical and intra-company applications. If we consider the distribution of classification and regression algorithms in the individual SCM task areas, it is notable that they are distributed differently. This is because, in SCD and SCE, categorical decisions are made, such as "is this supplier eligible - yes or no" or "is the quality acceptable - yes or no." In comparison, SCP deals with continuous questions, such as "how is demand evolving?" The equal distribution in SCC can be explained by the fact that both categorical and continuous issues are discussed in this SCM task domain. Unsupervised learning algorithms, however, are primarily used in the SCE domain. This is because image or video data, which is unstructured data, are often interpreted in the context of quality and production monitoring. The main application areas of ML in SCM are in supplier management, demand management and quality management, and it differ fundamentally in terms of the industry considered, data source, data types, and ML algorithms.

# References


Aamer, A. M., Yani, L. P. E. and Priyatna, I. M. A., 2020. Data Analytics in the Supply Chain Management: Review of Machine Learning Applications in Demand Forecasting. Operations and Supply Chain Management: An International Journal, pp. 1–13. http://dx.doi.org/10.31387/oscm0440281.

Abdollahnejadbarough, H., Mupparaju, K. S., Shah, S., Golding, C. P., Leites, A. C., Popp, T. D., Shroyer, E., Golany, Y. S., Robinson, A. G. and Akgun, V., 2020. Verizon Uses Advanced Analytics to Rationalize Its Tail Spend Suppliers. INFORMS Journal on Applied Analytics, [e-journal] 50(3), pp. 197–211. http://dx.doi.org/10.1287/inte.2020.1038.

Ahmadi, B., Javidi, B. and Shahbazmohamadi, S., 2018. Automated detection of counterfeit ICs using machine learning. Microelectronics Reliability, [e-journal] 88-90, pp. 371–377. http://dx.doi.org/10.1016/j.microrel.2018.06.083.

Alfian, G., Syafrudin, M., Farooq, U., Ma'arif, M. R., Syaekhoni, M. A., Fitriyani, N. L., Lee, J. and Rhee, J., 2020. Improving efficiency of RFID-based traceability system for perishable food by utilizing IoT sensors and machine learning model. Food Control, [e-journal] 110, p. 107016–107016. http://dx.doi.org/10.1016/j.foodcont.2019.107016.

Amirkolaii, K. N., Baboli, A., Shahzad, M. K. and Tonadre, R., 2017. Demand Forecasting for Irregular Demands in Business Aircraft Spare Parts Supply Chains by using Artificial Intelligence (AI). IFAC-PapersOnLine, [e-journal] 50(1), pp. 15221–15226. http://dx.doi.org/10.1016/j.ifacol.2017.08.2371.

Arksey, H. and O'Malley, L., 2005. Scoping studies: towards a methodological framework. International Journal of Social Research Methodology, [e-journal] 8(1), pp. 19–32. http://dx.doi.org/10.1080/1364557032000119616.

Babajanivalashedi, R., Baboli, A., Shahzad, M. K. and Tonadre, R., 2018. A Predictive Approach to Define the Best Forecasting Method for Spare Parts: A Case Study in Business Aircrafts' Industry. International Conference on Industrial Engineering and Engineering Management.

Badurdeen, F., Shuaib, M., Wijekoon, K., Brown, A., Faulkner, W., Amundson, J., Jawahir, I. S., J. Goldsby, T., Iyengar, D. and Boden, B., 2014. Quantitative modeling and analysis of supply chain risks using Bayesian theory. Journal of Manufacturing Technology Management, [e-journal] 25(5), pp. 631–654. http://dx.doi.org/10.1108/JMTM-10-2012-0097.

Baryannis, G., Dani, S. and Antoniou, G., 2019. Predicting supply chain risks using machine learning: The trade-off between performance and interpretability. Future Generation Computer Systems, [e-journal] 101, pp. 993–1004. http://dx.doi.org/10.1016/j.future.2019.07.059.

Baryannis, G., Validi, S., Dani, S. and Antoniou, G., 2019. Supply chain risk management and artificial intelligence: state of the art and future research directions. International Journal of Production Research, [e-journal] 57(7), pp. 2179–2202. http://dx.doi.org/10.1080/00207543.2018.1530476.

Becker, T. and Intoyoad, W., 2017. Context Aware Process Mining in Logistics. CIRP Conference on Manufacturing Systems.

Bhosekar, A. and Ierapetritou, M., 2021. A framework for supply chain optimization for modular manufacturing with production feasibility analysis. Computers & Chemical Engineering, [e-journal] 145, p. 107175–107175. http://dx.doi.org/10.1016/j.compchemeng.2020.107175.

Bousqaoui, H., Achchab, S. and Tikito, K., 2017. Machine Learning applications in supply chains. Piscataway, NJ: IEEE. Available at: Essaaidi, Mohammed (HerausgeberIn)

Zbakh, Mostapha (HerausgeberIn). <http://ieeexplore.ieee.org/servlet/opac?punumber=8277265>.

Brintrup, A., Pak, J., Ratiney, D., Pearce, T., Wichmann, P., Woodall, P. and McFarlane, D., 2019. Supply chain data analytics for predicting supplier disruptions: a case study in complex asset manufacturing. International Journal of Production Research, pp. 1–12. http://dx.doi.org/10.1080/00207543.2019.1685705.

Burggraf, P., Wagner, J. and Koke, B., 2018. Artificial intelligence in production management: A review of the current state of affairs and research trends in academia.

Cadavid, J. P. U., Lamouri, S. and Grabot, B., 2018. Trends in Machine Learning Applied to Demand & Sales Forecasting: A Review.

Calatayud, A., Mangan, J. and Christopher, M., 2019. The self-thinking supply chain. Supply Chain Management: An International Journal, [e-journal] 24(1), pp. 22–38. http://dx.doi.org/10.1108/SCM-03-2018-0136.

Cavalcante, I. M., Frazzon, E. M., Forcellini, F. A. and Ivanov, D., 2019. A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing. International Journal of Information Management, [e-journal] 49, pp. 86–97. http://dx.doi.org/10.1016/j.ijinfomgt.2019.03.004.

Diez-Olivan, A., Del Ser, J., Galar, D. and Sierra, B., 2019. Data fusion and machine learning for industrial prognosis: Trends and perspectives towards Industry 4.0. Information Fusion, [e-journal] 50, pp. 92–111. http://dx.doi.org/10.1016/j.inffus.2018.10.005.

Döring, A., Dangelmaier, W. and Danne, C., 2007. Using k-means for clustering in complex automotive production systems to support a Q-learning-system: ICCI 2007 August 6-8, 2007, Lake Tahoe, CA, USA. International Conference on Cognitive Informatics. Los Alamitos Calif.: IEEE Computer Society.

Durach, C. F., Kembro, J. and Wieland, A., 2017. A New Paradigm for Systematic Literature Reviews in Supply Chain Management. Journal of Supply Chain Management, [e-journal] 53(4), pp. 67–85. http://dx.doi.org/10.1111/jscm.12145.

Feizabadi, J., 2020. Machine learning demand forecasting and supply chain performance. International Journal of Logistics Research and Applications, pp. 1–24. http://dx.doi.org/10.1080/13675567.2020.1803246.

González Rodríguez, G., Gonzalez-Cava, J. M. and Méndez Pérez, J. A., 2019. An intelligent decision support system for production planning based on machine learning. Journal of Intelligent Manufacturing. http://dx.doi.org/10.1007/s10845-019-01510-y.

Gružauskas, V., Gimžauskienė, E. and Navickas, V., 2019. Forecasting accuracy influence on logistics clusters activities: The case of the food industry. Journal of Cleaner Production, [e-journal] 240, p. 118225–118225. http://dx.doi.org/10.1016/j.jclepro.2019.118225.

Hachimi, H. E. L., Oubrich, M. and Souissi, O., 2018. The optimization of Reverse Logistics activities: A Literature Review and Future Directions.

Hajek, P. and Abedin, M. Z., 2020. A Profit Function-Maximizing Inventory Backorder Prediction System Using Big Data Analytics. IEEE Access, [e-journal] 8, pp. 58982–58994. http://dx.doi.org/10.1109/ACCESS.2020.2983118.

Handfield, R., Sun, H. and Rothenberg, L., 2020. Assessing supply chain risk for apparel production in low cost countries using newsfeed analysis. Supply Chain Management: An International Journal, [e-journal] 25(6), pp. 803–821. http://dx.doi.org/10.1108/SCM-11-2019-0423.

Harikrishnakumar, R., Dand, A., Nannapaneni, S. and Krishnan, K., 2019. Supervised Machine Learning Approach for Effective Supplier Classification. International Conference on Machine Learning and Applications.

Hong, J., Yeo, H., Cho, N.-W. and Ahn, T., 2018. Identification of Core Suppliers Based on E-Invoice Data Using Supervised Machine Learning. Journal of Risk and Financial Management, [e-journal] 11(4), p. 70–70. http://dx.doi.org/10.3390/jrfm11040070.

Hosseini, S. and Ivanov, D., 2020. Bayesian networks for supply chain risk, resilience and ripple effect analysis: A literature review. Expert Systems with Applications, [e-journal] 161, p. 113649–113649. http://dx.doi.org/10.1016/j.eswa.2020.113649.

Kersten, W., von See, B. von, Lodemann, S. and Grotemeier, C., 2020. Trends und Strategien in Logistik und Supply Chain Management: Entwicklungen und Perspektiven einer nachhaltigen und digitalen Transformation.

Khalid, W. and Herbert-Hansen, Z. N. L., 2018. Using k-means clustering in international location decision. Journal of Global Operations and Strategic Sourcing, [e-journal] 11(3), pp. 274–300. http://dx.doi.org/10.1108/JGOSS-11-2017-0056.

Kilimci, Z. H., Akyuz, A. O., Uysal, M., Akyokus, S., Uysal, M. O., Atak Bulbul, B. and Ekmis, M. A., 2019. An Improved Demand Forecasting Model Using Deep Learning Approach and Proposed Decision Integration Strategy for Supply Chain. Complexity, [e-journal] 2019, pp. 1–15. http://dx.doi.org/10.1155/2019/9067367.

Kumar, R., Ganapathy, L., Gokhale, R. and Tiwari, M. K., 2020. Quantitative approaches for the integration of production and distribution planning in the supply chain: a systematic literature review. International Journal of Production Research, [e-journal] 58(11), pp. 3527–3553. http://dx.doi.org/10.1080/00207543.2020.1762019.

Levac, D., Colquhoun, H. and O'Brien, K. K., 2010. Scoping studies: advancing the methodology. Implementation science : IS, [e-journal] 5, p. 69–69. http://dx.doi.org/10.1186/1748-5908-5-69.

Li, J., Moghaddam, M. and Nof, S. Y., 2016. Dynamic storage assignment with product affinity and ABC classification—a case study. The International Journal of Advanced Manufacturing Technology, [e-journal] 84(9-12), pp. 2179–2194. http://dx.doi.org/10.1007/s00170-015-7806-7.

Li, Z., Guo, H., Barenji, A. V., Wang, W. M., Guan, Y. and Huang, G. Q., 2020. A sustainable production capability evaluation mechanism based on blockchain, LSTM, analytic hierarchy process for supply chain network. International Journal of Production Research, pp. 1–21. http://dx.doi.org/10.1080/00207543.2020.1740342.

Ma, H., Wang, Y. and Wang, K., 2018. Automatic detection of false positive RFID readings using machine learning algorithms. Expert Systems with Applications, [e-journal] 91, pp. 442–451. http://dx.doi.org/10.1016/j.eswa.2017.09.021.

Marsland, S., 2014. Machine Learning: An Algorithmic Perspective, Second Edition. 2nd ed. [e-book]. Hoboken: CRC Press. <http://gbv.eblib.com/patron/FullRecord.aspx?p=1591570>.

Meiners, M., Mayr, A., Lechler, T. and Franke, J., 2019. Accelerated Production Ramp-Up Utilising Clustering and Visualisation of Process Chain Interrelationships. International Electric Drives Production Conference.

Munn, Z., Peters, M. D. J., Stern, C., Tufanaru, C., McArthur, A. and Aromataris, E., 2018. Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach. BMC medical research methodology, [e-journal] 18(1), p. 143–143. http://dx.doi.org/10.1186/s12874-018-0611-x.

Myles D., G., Steven, C. and Sengun, Y., 2015. An Analytical Framework for Supply Network Risk Propagation: A Bayesian Network Approach. European Journal of Operational Research.

Nguyen, T., Zhou, L., Spiegler, V., Ieromonachou, P. and Lin, Y., 2018. Big data analytics in supply chain management: A state-of-the-art literature review. Computers &

Operations Research, [e-journal] 98, pp. 254–264. http://dx.doi.org/10.1016/j.cor.2017.07.004.

Ni, D., Xiao, Z. and Lim, M. K., 2020. A systematic review of the research trends of machine learning in supply chain management. International Journal of Machine Learning and Cybernetics, [e-journal] 11(7), pp. 1463–1482. http://dx.doi.org/10.1007/s13042-019-01050-0.

Ojha, R., Ghadge, A., Tiwari, M. K. and Bititci, U. S., 2018. Bayesian network modelling for supply chain risk propagation. International Journal of Production Research, [e-journal] 56(17), pp. 5795–5819. http://dx.doi.org/10.1080/00207543.2018.1467059.

Okaro, I. A., Jayasinghe, S., Sutcliffe, C., Black, K., Paoletti, P. and Green, P. L., 2019. Automatic fault detection for laser powder-bed fusion using semi-supervised machine learning. Additive Manufacturing, [e-journal] 27, pp. 42–53. http://dx.doi.org/10.1016/j.addma.2019.01.006.

Peng, Z., Zhang, Y., Feng, Y., Zhang, T., Wu, Z. and Su, H., 2019. Deep Reinforcement Learning Approach for Capacitated Supply Chain optimization under Demand Uncertainty. Chinese Automation Congress.

Pereira, M. M. and Frazzon, E. M., 2020. A data-driven approach to adaptive synchronization of demand and supply in omni-channel retail supply chains. International Journal of Information Management, p. 102165–102165. http://dx.doi.org/10.1016/j.ijinfomgt.2020.102165.

Priore, P., Ponte, B., Rosillo, R. and La Fuente, D. de, 2019. Applying machine learning to the dynamic selection of replenishment policies in fast-changing supply chain environments. International Journal of Production Research, [e-journal] 57(11), pp. 3663–3677. http://dx.doi.org/10.1080/00207543.2018.1552369.

Priyadarshi, R., Panigrahi, A., Routroy, S. and Garg, G. K., 2019. Demand forecasting at retail stage for selected vegetables: a performance analysis. Journal of Modelling in Management, [e-journal] 14(4), pp. 1042–1063. http://dx.doi.org/10.1108/JM2-11-2018-0192.

Sabbagh, R. and Ameri, F., 2018. Supplier Clustering Based on Unstructured Manufacturing Capability Data. International Design Engineering Technical Conferences and Computers and Information in Engineering Conference.

Sabbagh, R. and Ameri, F., 2020. A Framework Based on K-Means Clustering and Topic Modeling for Analyzing Unstructured Manufacturing Capability Data. Journal of Computing and Information Science in Engineering, [e-journal] 20(1). http://dx.doi.org/10.1115/1.4044506.

Sasaki, H. and Sakata, I., 2020. Business partner selection considering supply-chain centralities and causalities. Supply Chain Forum: An International Journal, pp. 1–12. http://dx.doi.org/10.1080/16258312.2020.1824531.

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

Simeone, A., Zeng, Y. and Caggiano, A., 2020. Intelligent decision-making support system for manufacturing solution recommendation in a cloud framework. The International Journal of Advanced Manufacturing Technology. http://dx.doi.org/10.1007/s00170-020-06389-1.

ten Hompel, M. and Hellingrath, B., 2007. IT & Forecasting in Industrie und Handel. 24. Deutscher Logistik-Kongress Berlin, pp. 281–310.

ten Hompel, M., Wolf, O., Nettsträger, A., Ebel, D., Geissen, T., Kraft, V., MErtens, C., Pott, C., Schoneboom, J. and Witthaut, M., 2013. IT in der Logistik 2013 / 2014: Marktübersicht & Funktionsumfang: Enterprise-Resource.Planning, Warehouse-Management, Marktübersicht & Funktionsumfang: Enterprise-Resource.Planning, Warehouse-Management, Transport-Management & Supply-Chain-Management-Systeme.

Tranfield, D., Denyer, D. and Smart, P., 2003. Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. British Journal of Management, [e-journal] 14(3), pp. 207–222. http://dx.doi.org/10.1111/1467-8551.00375.

United Nations, 2008. International Standard industrial classification of all economic activities (ISIC). 4th ed. New York: United Nations.

Vanvuchelen, N., Gijsbrechts, J. and Boute, R., 2020. Use of Proximal Policy Optimization for the Joint Replenishment Problem. Computers in Industry, [e-journal] 119, p. 103239–103239. http://dx.doi.org/10.1016/j.compind.2020.103239.

Wang, C.-H. and Chen, T.-Y., 2020. Combining biased regression with machine learning to conduct supply chain forecasting and analytics for printing circuit board. International Journal of Systems Science: Operations & Logistics, pp. 1–12. http://dx.doi.org/10.1080/23302674.2020.1859157.

Wenzel, H., Smit, D. and Sardesai, S., 2019. A Literature Review on Machine Learning in Supply Chain Management, pp. 412–441.

Wichmann, P., Brintrup, A., Baker, S., Woodall, P. and McFarlane, D., 2020. Extracting supply chain maps from news articles using deep neural networks. International Journal of Production Research, pp. 1–17. http://dx.doi.org/10.1080/00207543.2020.1720925.

Wilson, V. H., Prasad, A., Shankharan, A., Kapoor, S. and Rajan, J., 2020. Ranking of supplier performance using machine learning algorithm of random forest.

Wohlin, C., 2014. Guidelines for snowballing in systematic literature studies and a replication in software engineering. In: M. Shepperd, T. Hall, and I. Myrtveit. Proceedings of the 18th International Conference on Evaluation and Assessment in Software Engineering - EASE '14. the 18th International Conference. London, England, United Kingdom, 13.05.2014 - 14.05.2014. New York, New York, USA: ACM Press, pp. 1–10.

Wu, C., Lin, C., Barnes, D. and Zhang, Y., 2020. Partner selection in sustainable supply chains: A fuzzy ensemble learning model. Journal of Cleaner Production, [e-journal] 275, p. 123165–123165. http://dx.doi.org/10.1016/j.jclepro.2020.123165.

Zakeri, A., Saberi, M., Hussain, O. K. and Chang, E., 2018. An Early Detection System for Proactive Management of Raw Milk Quality: An Australian Case Study. IEEE Access, [e-journal] 6, pp. 64333–64349. http://dx.doi.org/10.1109/ACCESS.2018.2877970.

Zgodavova, K., Bober, P., Majstorovic, V., Monkova, K., Santos, G. and Juhaszova, D., 2020. Innovative Methods for Small Mixed Batches Production System Improvement: The Case of a Bakery Machine Manufacturer. Sustainability, [e-journal] 12(15), p. 6266–6266. http://dx.doi.org/10.3390/su12156266.

Zhang, G., Li, G. and Peng, J., 2020. Risk Assessment and Monitoring of Green Logistics for Fresh Produce Based on a Support Vector Machine. Sustainability, [e-journal] 12(18), p. 7569–7569. http://dx.doi.org/10.3390/su12187569.

Zhang, Y. and Bhattacharyya, S., 2007. Effectiveness of Q-learning as a tool for calibrating agent-based supply network models. Enterprise Information Systems, [e-journal] 1(2), pp. 217–233. http://dx.doi.org/10.1080/17517570701275390.